

PLANNING OPTIMAL PLEA BARGAINING  
AND SENTENCING STRATEGIES FOR  
A STATE JUDICIARY

A THESIS

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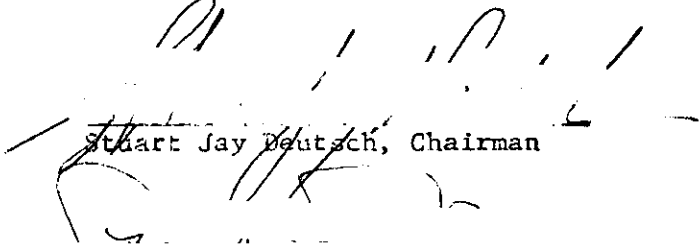
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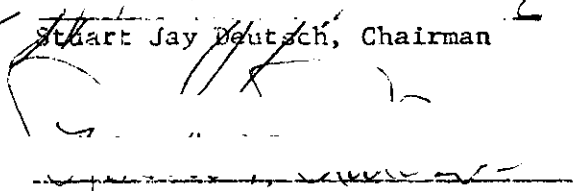
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A STATE JUDICIARY

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# ERRATA

In numbering this document's pages, pages 11 and 213 were omitted.

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## SUMMARY

The models which are currently being used to evaluate the performance of the Criminal Justice System have several limitations and each generally focuses on a specific problem area. The objective of this research is to develop a state-of-the-art discrete event simulation model which combines many of the strengths of earlier works and which may be used as a general tool for performance evaluation. Tracing the criminal careers of offenders from the time of their first arrest until their career in crime ends, the model structurally mimics a representative CJS with a recidivism component to allow for an offender's re-arrest. The Generalized Network Simulator (GNS) is the vehicle for implementation so that queueing, resource allocation and cost issues can also be considered.

A quasi-experimental design examining plea bargaining alternatives demonstrates the model's utility in evaluating CJS performance. A linear career criminal social cost function is postulated which combines measures of recidivism and CJS cost. By minimizing the career criminal social cost for different sets of importance weights for male and female offenders, this research indicates that having the prosecutor make plea bargaining decisions based upon the number of offenses in an offender's arrest record results in a significant savings over scenarios in which this information is not available or in which an a priori measure of the severity of a crime category is used as

a basis for the prosecutor's decision. This analysis also shows that each policy alternative affects different subpopulations of offenders in different manners; thus, the choice of the importance weights not only determines the optimal policy, but it also raises the issue of equity in dealing with offender subpopulations.

## CHAPTER I

### INTRODUCTION

#### 1.1 Problem Description

The incidence of reported crime has been growing in the United States at a rate which greatly exceeds the growth in the nation's population. During the five year period beginning in 1969, for example, the number of crimes against property per 1000 persons rose 31% above the 1969 rate while the number of violent crimes per 1000 population increased 40% over the same period [29; pp. 13-14]. With the level of crime increasing at such rates, the federal government initiated efforts to study the problem with the appointment of a presidential commission, and in 1967 the Commission on Law Enforcement and the Administration of Justice published its reports [54] [55]. One lasting result of the Commission's work was the demonstration that empirical models can be used effectively in the evaluation of the Criminal Justice System (CJS) as society's instrument for controlling crime. Two varieties of empirical models were used by the Commission's Task Force on Science and Technology to evaluate the performance of the Criminal Justice System. A simulation model of the District of Columbia federal court was used to evaluate the effects of delays in the courts; analytical models developed by Christensen were used to develop estimates of the rate of recidivism and of the number of arrests per lifetime of those offenders who recidivate [54].

Both the simulation and the analytical models reported by the Commission have had considerable impact on policy analysts from the view-

point of their acceptance of such methods for the evaluation of the Criminal Justice System's performance, but the work of Christensen in particular also yielded important insights of a criminological nature. The estimates that he developed indicated that a large percentage of those offenders who are arrested once will be re-arrested for several additional crimes later in life. In response to the findings of Christensen and others [80], CJS administrators have attempted to combat this inadequacy of the Criminal Justice System by implementing special programs designed to reduce the so-called career criminal's opportunities to commit offenses. One effort currently financed by the federal government specifically attempts to decrease the time that the career criminal is free to commit offenses by simultaneously increasing his chances for conviction and by increasing the expected length of his prison sentence. Although these objectives appear to have been realized with the establishment of special prosecutors whose caseloads consist only of recidivists [68] [76] [65], the methods of evaluating such programs generally rely on the analytical techniques of modeling the careers of offenders.

The analytical models which have been used to date for this purpose, however, possess several shortcomings. One deficiency of these models is their need to possess aggregate parameters which greatly simplify the arrest, conviction, release, and recidivism processes. In addition, very little attention is devoted in analytical models to the characteristics of different offender types other than to the first offender - recidivist dichotomy. These two shortcomings in modeling criminal careers not only limit the evaluative efforts for career

criminal programs, but they also inhibit the innovative policy analyst from experimenting with proposed programs or operating procedures.

### 1.2 Purpose of the Research

To overcome the deficiencies in the evaluation methods currently in use, it is the objective of this research to develop a digital simulation model of an idealized Criminal Justice System that traces the entire criminal careers of arrested first offenders. Although the use of simulation models in Criminal Justice planning is not new, this model is the first known implementation of a digital simulator which includes several descriptors for each simulated offender, which is of sufficient detail structurally to mimic the actual flows of offenders throughout the Criminal Justice System for their entire criminal careers, and which describes the completed offender careers in terms of such factors as the average number of offenses per offender and the average cost of processing an offender over his entire criminal career. These offenders are distinguished from those of earlier simulations in that they are characterized by their age, sex, current offense, and number and type of previous offenses. The simulator which has been selected for this model is the Generalized Network Simulator (GNS). The capabilities of this simulator are such that it is ideally suited for the modeling of large scale systems. By combining the queueing, resource allocation, and costing features of GNS into the model of the Criminal Justice System, the resulting tool is a sophisticated tool for policy evaluation and analysis.

In addition to developing such a model, an example of how it can



be used to evaluate policy alternatives is also addressed. Using data originating primarily from the Sacramento County, California Criminal Justice System, alternate policy scenarios for plea bargaining are examined. The choice of plea bargaining as the topic for experimental analysis is predicated on its centrality in the adjudication process. Of all the cases in the U.S. District Courts that result in convictions, as much as 89% of those convicted for index offenses in 1975 were determined by the defendant negotiating a plea of guilty [74; pp. 603]. This remarkably high percentage indicates that a great deal of plea negotiations must be taking place, thereby tending to reduce prison sentences and, ostensibly, increasing the number of re-arrests during a criminal career. Therefore, it is only natural that research designed to impact the career criminal begin with an evaluation of the present plea bargaining model with additional analysis directed at alternatives to the present arrangement.

Although the analysis of the plea bargaining scenarios is not to be construed to be a definitive treatment of the topic or of its alternatives, the principal purpose for its inclusion in this research is to highlight the potential uses of a career criminal - oriented digital simulation model of the type developed for this research. In the evaluation of the policy alternatives, sample output from the model is examined and additional analyses are performed which might be of use to an analyst attempting to evaluate policy alternatives which impact recidivism and, in particular, the career criminal.

### 1.3 Overview of the Research

The organization of this research is as follows. In Chapter II and in the first two sections of Chapter III is discussed the important literature upon which this thesis is based. Specifically, Chapter II discusses the analytical and simulation models beginning with the Commission's efforts which have been used to examine aspects of CJS performance. In Chapter III, on the other hand, the mechanics of plea bargaining is examined with an eye intent on simulating alternative policy scenarios. Two economic models of plea bargaining are addressed which shed considerable light on how this process may actually work and on how it may be simulated with some credibility. This analysis leads to the formulation of a model in the last section of Chapter III which attempts to describe how the prosecutor would respond to two measures which are important to career criminal programs, an offender's previous arrest record and the severity of his most recent offense.

In Chapter IV the Generalized Network Simulation model is developed which traces arrested offenders, both juveniles and adults, from the moment of their first arrest until the time when they are released from the system, having desisted in their criminal careers. The GNS network representation of the model is given and the details of the model's processors are described.

The implementation of the model is then discussed in Chapter V. To begin, the data used for the analysis of plea bargaining is first described. Then, the model's queues are initialized and the Criminal Justice System's resources are allocated to the model's processors; finally, the model's validity is evaluated for its ability to mimic

observable phenomena as well as for its own internal consistency.

In as much as Chapters IV and V are devoted to the description, implementation, and validation of the model, Chapter VI returns to the issue of plea bargaining. This chapter addresses itself to the formulation and testing of alternative plea bargaining scenarios designed to simultaneously reduce the average number of offenses of the criminal career of both sexes and the average cost of processing these offenders over their entire criminal careers. Sample outputs from the model are evaluated at this time and sensitivity analyses are conducted on the cost model's parameters.

Finally, Chapter VII concludes this research by summarizing the important results and by offering suggested avenues for additional work in this area. In addition, the insights derived from the evaluation of plea bargaining, both from the modeling and the administrative points of view, are discussed and recommendations offered.

## CHAPTER II

### A SURVEY OF CRIMINAL JUSTICE SYSTEM MODELS

#### 2.0 Introduction

In order to develop the simulation model of the Criminal Justice System described in Chapter I a thorough understanding is required of the quantitative techniques which have already been used to evaluate the system's performance. That is the purpose of this chapter: to survey those models which have had considerable impact on CJS modeling and on system - level performance measurement. Two distinct classes of models are identified in this survey. The first class is composed of models which are analytical in nature. These models have been used for describing the composition of the offender population (career criminals versus one-time offenders) and for predicting the recidivism rate of career criminals. The latest generation of these models is currently being used to evaluate these performance measures for several metropolitan systems in this country.

Another class of CJS models which have been used for planning and evaluation purposes, are digital simulation models. Because of the flexibility of the simulation method, these models have been used variously for forecasting resource requirements, for evaluating delays in processing offenders, and for examining the effects of alternative parameter specifications on resource requirements and on recidivism. None of these models, however, has been used with the detail given to describing the offender that is proposed for the model developed in this research. Furthermore,

only one simulation model has already been developed which integrates the queueing and costing factors which are envisioned for this model, but the earlier effort was abandoned without having been fully implemented.

To begin this summary of CJS models, the analytical models are addressed first.

### 2.1 Analytical Models

The analytical model form first appeared in the 1967 Presidential Commission's Task Force Report: Science and Technology [54]. Christensen was the author of several simple but illuminating models which described the percentage of the offender population which recidivated and which approximated the number of arrests that could be expected during any recidivists criminal career. Although Christensen's models were simplistic in nature, they did spark the imagination of other modelers who have developed not only descriptive models but also models which include policy variables. The analytical models that have appeared in the Criminal Justice literature are aggregate in nature; because of the need to obtain mathematical solutions to such complex phenomena, these models generally limit the analyst to addressing policy scenarios which are specific and which assume little interaction among the policy variables. These models can be characterized by:

1. A high level of aggregation,
2. An assumed-homogeneous criminal population,
3. An assumption of steady-state,
4. Time invariant parameters,

5. A lack of consideration of CJS costs and resource usage.

#### 2.1.1 Early Models of Offenders

Christensen's analysis that appeared in the Task Force Report: Science and Technology [54] was pioneering because it showed that, by using simple mathematical models to describe a criminal career and the composition of the offender population, a great deal of information can be gleaned from such an analysis. His work is most noteworthy for his development of models of an offender's career in crime. Initially, he devised a crude forecasting function for the number of offenders who are arrested each year who have never before been arrested. Using information derived from this forecasting function, he then formulated and estimated the parameters of a probabilistic model of the number of arrests that occur during an offender's criminal career. Finally, his other major contribution was the derivation of an estimate for the incapacitative effect of the CJS over an offender's lifetime. Although his models have not specifically re-appeared in the literature, Christensen's pioneering efforts have served as a source of insight for several subsequent models which are currently being used to evaluate the Criminal Justice System.

Christensen developed forecasts of the percentage of the U.S. population that had been arrested at least once. He assumed that the probability of the first arrest is dependent upon the offender's age  $a$  and upon the offender's ability to survive to that age. The joint probability that a person is arrested for the first time and that he is an  $a$ -year-old was defined as

$$P_a = L_a \left( \frac{V_a}{M_a} \right),$$

where  $L_a$  is the probability that a person survives to age  $a$ ,  $V_a$  is the number of first offenders who are arrested at age  $a$ ,  $M_a$  is the size of the entire population whose age is  $a$ , and the ratio

$$p(a) = \frac{V_a}{M_a} \quad (2-1)$$

is the probability that an offender is first arrested at age  $a$ . By assuming that  $L_a$  and  $p(a)$  are both time invariant, Christensen could forecast the number of persons who are arrested for the first time (called virgin arrestees) during any year  $t$ . With a forecast of the U.S. population  $\hat{M}_a(t)$ , the virgin arrest forecast could then be computed as

$$\hat{F}(t) = \sum_{a=0}^{d'} p_a \hat{M}_a(t) , \quad (2-2)$$

where  $d'$  is the age beyond which people are no longer arrested.

Since  $L_a$ ,  $M_a$ , and  $\hat{M}_a(t)$  were all available at the time, Christensen only needed to approximate  $V_a$  to determine the forecast function. To accomplish this, he first estimated the virgin arrest fraction  $r_a$  as a function of age using 1965 juvenile data collected from the Philadelphia County Court. This fraction was then multiplied by  $N_a$ , the number of arrests of  $a$ -year-olds reported in the 1965 Uniform Crime Reports (UCR). The resulting product is the number of virgin arrests who are  $a$  years old,

$$V_a = r_a N_a . \quad (2-3)$$

(Christensen also had to adjust  $V_a$  for the limited coverage of the FBI Uniform Crime Report [29] statistics; he did so by multiplying  $V_a$  by the

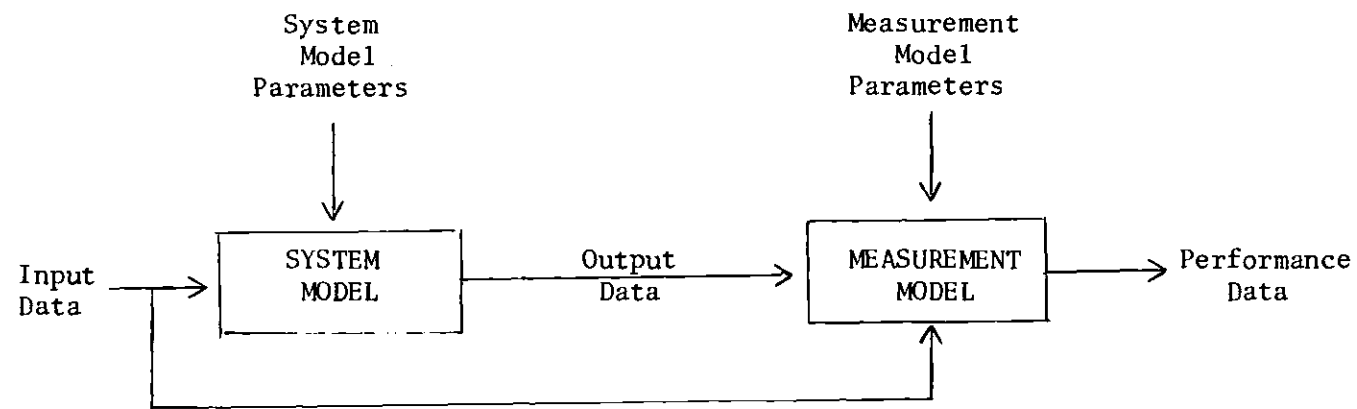


Figure 1. A Single-Input, Single-Output Simulation Model



ratio of the U.S. population to the statistical population in order to derive a forecast for the entire U.S.)

Pursuing the arrest issue further, Christensen also developed a crude model of offender recidivism. Using data from the District of Columbia, he determined empirically that the number of arrests during an offender's criminal career is best described by an exponential function of the form

$$x = \Gamma e^{-n/b}, \quad (2-4)$$

where  $x$  is the percentage of the population arrested at least  $n$  times,  $n$  is the expected number of arrests during an offender's lifetime,  $b$  is the average number of arrests of offenders who are arrested at least once, and  $\Gamma$  is the maximum probability of the exponential distribution function. For adult males, he estimated  $\Gamma_m = 50\%$  and  $b_m = 7.6$  while for adult females,  $\Gamma_f = 13\%$  and  $b_f = 3.8$ .

Defining  $P_i$  as the probability that a person who was arrested  $i$  times will be arrested  $(i + 1)$  times, then

$$P_i = \frac{x(n+1)}{x(n)},$$

for  $n \geq 0$ . But substituting the definition of  $x$  into the above equation, this probability is

$$P_i = e^{-1/b}. \quad (2-5)$$

For adult male offenders,  $b = 7.6$  results in  $P_i = .88$  for all  $i \geq 1$ . This clearly demonstrates that one-time male offenders are distinctly different from multiple offenders since  $P_0 = \Gamma_m = .5$ . In addition, it

destroys the notion that  $x$  is Poisson distributed, since such a high correlation between subsequent arrests violates the assumption of independent events required for a Poisson process.

Christensen also determined the percentage of the U.S. population which was convicted at least once. Since its derivation is similar to that of the percentage arrested, it will also not be described here. There was, however, an off shoot of the conviction analysis which deserves mentioning in as much as it re-appears in various forms in several later models. The subject of this recurring theme is offender incapacitation. Although Christensen did not specifically analyze the incapacitation effect of the CJS, he did develop a simplistic model to estimate the average number of years that an offender is under the care of the corrections subsystem.

The model he developed is based upon his findings that approximately  $f = 12\%$  of the total U.S. population  $U$  is eventually convicted of a crime; the expression for the number of people in the U.S. that are eventually convicted is

$$C = fU. \quad (2-6)$$

Estimating  $g$ , the fraction of the U.S. population which is supervised by corrections at any point in time, the expression for the number supervised is

$$S = gU.$$

Christensen found, by defining  $L$  as the average lifetime of a U.S. resident (in years) and  $T$  as the average time that a convict is in prison, that

$$C = \frac{L}{T} S \quad (2-7)$$

can also be used to describe the number of persons eventually convicted, assuming that the ages of those being supervised is uniformly distributed between their birthdays and age L. Equating the two expressions for C and solving for T results in an estimate of the incapacitation effect of the CJS:

$$T = \frac{LgU}{fU} = \frac{Lg}{f} . \quad (2-8)$$

By assuming L = 70, Christensen determined that the average time that a convicted offender spent under the supervision of corrections was T = 4 years.

Thus, Christensen fathered the idea that analytical techniques can be used to estimate the characteristics of the offender population. His work has led to several models which have combined his description of virgin offenders and recidivists into a unified formulation of the criminal career. Eventually, his successors were able to incorporate deterrence and incapacitation functions into the model of the criminal career. Thus, the use of such models for the evaluation of alternate policy scenarios is based upon the impact of Christensen's work for the President's Commission on the Criminal Justice community.

#### 2.1.2 A Feedback Model of Recidivism

Belkin, Blumstein and Glass [9] were some of Christensen's earliest successors in applying analytical techniques to the control of crime. They developed a feedback model of the CJS. Although their model contained only two components of the CJS, a combined police and judicial component and a corrections component, their objective was to model the entire

criminal career. Thus, the feedback in the model is the flow of recidivists back into the police subsystem (viz, their re-arrest following their release from the CJS. Offenders released from the police-court component are re-arrested with probability  $\alpha_1$  following  $\tau_1$  elapsed years whereas offenders who are released from corrections are re-arrested after  $\tau_2$  years with probability  $\alpha_2$ . The delays  $\tau_1$  and  $\tau_2$  were both assumed to be the mean values of negative exponential distributions; however, Stollmack and Harris [64] were later to demonstrate that the delay between an offender's release from the CJS and his subsequent re-arrest can in fact be described by the negative exponential distribution. Because the time an offender spends in prison was found to be approximately one year, the following relationship was assumed:

$$\tau_2 = \tau_1 + 1.$$

Belkin, Blumstein and Glass determined the model's input  $V(t)$ , the number of virgin arrests at time  $t$ , by using the relation

$$V(t) = \int_a p(a) U(a,t) \quad (2-9)$$

where  $p(a)$  is the probability of a first-offense arrest at age  $a$  and  $U(a,t)$  is the number of people in the U.S. who are  $a$ -years-old at time  $t$ . To derive an estimate of  $p(a)$  for all  $a$ , they combined Christensen's estimate of  $p(a)$  in equation 2-1 for adult offenders with an estimate derived from a longitudinal study of adolescent males conducted by Wolfgang, Figlio and Sellin [80].

Belkin, Blumstein and Glass used their model of the CJS to analyze the recidivism process. For simplicity, they assumed that  $\alpha_1 = \alpha_2 = \alpha$

(i.e., that rehabilitative and special deterrence effects of corrections are non-existent). By conducting parametric studies, they were able to determine a "best" fit between the total number of arrests predicted by the model,  $N(t)$ , and the FBI's statistics over the period between 1960 and 1970. The parametric analysis resulted in the estimates  $\alpha = .875$  and  $\tau_1 = 1.1$  years. Further analysis of the FBI's data, however, showed that the data was quadratic. To test this observation, they hypothesized that  $p(a)$  varied with time, and they re-evaluated the virgin arrest rate by adding a linear growth term to the old estimate:

$$V'(t) = V(t) + (t - 1963)G$$

where  $G$  is an empirically-determined rate of growth which they assumed began in 1963. Next, these analysts examined the fit between the model's  $N'(t)$  and the FBI's statistics. They discovered that  $\alpha' = .86$  and  $\tau_1 = 1.2$  minimized the average percent deviation between the model - generated and the actual data, and they concluded that the magnitude of  $p(a)$  had increased over time with a concomitant decline in  $\alpha$ , the re-arrest probability. That is, the level of crime committed by first-offenders had increased while recidivism had declined.

Analyzing their model during steady state, Belkin, Blumstein and Glass determined that

$$N(t) = \frac{V(t)}{1 - \alpha} . \quad (2-10)$$

By defining  $u = (1 - \alpha)^{-1}$ , they further determined that

$$\frac{d N(t)}{N(t)} = \frac{d V(t)}{V(t)} + \frac{du}{u} . \quad (2-11)$$

This last equation specifies that a percentage increase either in the virgin arrest rate,  $V(t)$ , or in  $u$  causes the same percentage increase in  $N(t)$ . Thus, a 10% reduction in  $V(t)$  is approximately equivalent to a 5% reduction in  $\alpha$ , an insight of considerable importance to policy analysts.

To be sure, Belkin, Blumstein and Glass's model and accompanying analyses reached a much greater level of sophistication than those of Christensen. They demonstrated that recidivism can be modeled. In addition, they showed that important insights can be acquired by re-examining the model's assumptions and by evaluating the effects of parameter changes on the model's performance measures. This work has also shown CJS planners that reducing the rate of recidivism is a much more effective method of reducing the total level of crime than is reducing the virgin arrest rate. Unfortunately, this model does not tell the CJS planner how to reduce recidivism. Nor does it give any hint as to the alternatives which are the least costly. These important performance measures, it will be seen, are lacking in each of the analytical models surveyed. It is not until the simulation models that such issues are addressed.

### 2.1.3 A Policy Model Involving Incapacitation

The first model which possessed recognizable policy variables was developed by Avi-Itzhak and Shinnar [5] and it was subsequently refined by Shinnar and Shinnar [63]. The resulting model is similar to the Christensen and to the Belkin, Blumstein and Glass models in that it portrays the recidivism process; however, it was not developed as a model of the Criminal Justice System. Rather, Avi-Itzhak and Shinnar modeled

the criminal career of an offender and incorporated the incapacitation effect of the CJS into the model formulation. Two policy variables were included in the formulation, the length of incarceration and the effectiveness of the police and the prosecution. For simplicity, the processes being modeled were assumed to be in steady state. Although it was discovered that the steady state assumption is not valid, this does not necessarily detract from the model itself. Indeed, as was shown earlier for Belkin, Blumstein and Glass's model, useful insights are oftentimes gained from such models.

Despite the fact that Christensen had shown that offenders are arrested according to a negative exponential distribution, Avi-Itzhak and Shinnar assume that an offender commits  $\lambda$  offenses per year according to a Poisson distribution. This apparent discrepancy can be justified by assuming that the crime commission process is in fact composed of independent criminal acts, whereas the process of arresting offenders is no longer independent of the number of previous arrests of each offender. It seems quite reasonable to assume that the police would more likely suspect and consequently arrest an offender who has been arrested at least once. This also may explain the existence of the high correlation between an offender's arrests numbered two and above.

Avi-Itzhak and Shinnar were able to specify the number of crimes,  $x$ , committed by a criminal during his career in crime by assuming each criminal career is exponentially distributed with an average length  $T$ . (They also showed that a constant career length gives approximately the same results.) Thus, if the CJS does not affect the behavior of the offender (viz, through deterrence, incapacitation or rehabilitation),

then the expected number of crimes committed by an offender is

$$E(x) = \lambda T.$$

Because Avi-Itzhak and Shinnar's objective was to describe the effect that the CJS has upon the offender's criminal career, they developed the following model.

First, these two modelers defined a parameter  $q$ , the joint probability that an offender is both arrested and convicted following his commission of a crime. This parameter is one of the model's policy variables since changing the effectiveness of either the police or the prosecution changes the value of  $q$ . For simplicity,  $q$  is assumed to be constant for each offense, i.e., the police and the prosecutor do not become more effective as an offender commits additional offenses. By defining  $J$  to be the conditional probability that an offender is incarcerated following his conviction, and  $S$  as the actual time served in prison, the product  $qJ$  becomes the conditional probability that an offender is imprisoned following his commission of a crime and  $qJS$  is the average detention (incapacitation) time for each offense. The ratio  $(\lambda qJ)^{-1}$  is the average time that each offender is not in prison.

Avi-Itzhak and Shinnar approximated the fraction of the time that an offender is free to commit offenses by the expression,

$$\frac{(\lambda qJ)^{-1}}{(\lambda qJ)^{-1} + S} = \frac{1}{1 + \lambda qJS}.$$

At a later date, Shinnar and Shinnar [63] showed that this relationship is more precise for  $T \gg S$ ; otherwise, the expression overestimates the



actual ratio. Assuming that an incapacitation effect actually exists, the expected number of crimes that an offender commits becomes

$$E(x) = \frac{\lambda T}{1 + \lambda qJS} \quad (2-12)$$

and the effectiveness of the CJS in reducing crime is

$$T = 1 - \frac{1}{1 + \lambda qJS} . \quad (2-13)$$

This result of Avi-Itzhak and Shinnar's model is striking, because their model is immediately a tool for testing CJS policy, both new and proposed. In particular, sentencing alternatives and police and prosecution effectiveness can be varied under scenarios designed to maximize  $T$ . Once again, however, independent studies would have to determine the cost effectiveness of each policy alternative as a cost model is not presently available for any of the analytical models surveyed.

Avi-Itzhak and Shinnar were able to evaluate the sensitivity of their model to changes in policy by defining " $N^{\text{th}}$  time out" equivalent systems. This equivalence exists when an offender is assumed not to be sentenced to prison for the first  $(N-1)$  times that he is convicted. That is, for the first  $(N-1)$  convictions  $S_c = 0$ ,  $c=1,2,\dots,N-1$ . For the  $N^{\text{th}}$  conviction, the offender is assumed to be sentenced to prison for the remainder of his life; thus,  $S_N = \infty$ . Assuming that  $S$  is an exponentially distributed random variable with  $E(s) = \frac{1}{\mu_s}$ , Avi-Itzhak and Shinnar were able to determine the  $N^{\text{th}}$  time out equivalent model's sensitivity to the policy variables  $q$  and  $\frac{1}{\mu_s}$ . Their results show that  $N$  decreases if either

the release to conviction recidivism probability,

$$1 - P = \frac{\lambda q}{1 + \lambda q} \quad (2-14)$$

decreases or if the expected sentence length  $\frac{1}{\mu_s}$  increases. The greatest reduction in  $N$  is achieved for simultaneously large values of  $1-P$  (that is, large  $q$ ) and small values of  $\frac{1}{\mu_s}$ . For both small values of  $1-P$  and large  $\frac{1}{\mu_s}$ ,  $N$  varies relatively little.

Thus, Avi-Itzhak and Shinnar developed a model dealing with an offender's criminal career, and they were able to determine the impact of the CJS on the number of offenses committed per offender. This model is a powerful tool because of its ability to relate the expected number of offenses per offender,  $E(x)$ , to the policy variables  $q$  and  $S$ . As with other models of this type, however, the model is highly aggregate and, as a consequence, it does not have the ability to differentiate between the treatment of offenders who, for example, commit different offenses. Hence, the parameters  $q$ ,  $J$ , and  $S$  must be estimated separately for each offender category in order to examine differential treatment; but, this approach hinders the analysis of dynamic behavior like the crime switching phenomena observed by Wolfgang, et al. [80] and Blumstein and Larson [12]. To be sure, then, the high level of aggregation reduces the utility of such a model for policy evaluation studies. In addition, the lack of cost and resource considerations excludes the criterion of an incremental crime reduction per incremental cost; a separate cost model must be added to afford meaningful cost estimates.

#### 2.1.4 A Policy Model Involving Deterrence and Incapacitation

The most recent advance in analytic models of the operations of

the CJS, a policy model developed by Blumstein and Nagin examines the incapacitative as well as the deterrent effects of incarceration [14]. Their model borrows directly from Avi-Itzhak and Shinnar's formulation of offender incapacitation; however; the insights and analysis of Ehrlich [27][28] concerning the existence of a deterrent effect undoubtedly stimulated their research. Ehrlich built a utility - theoretical model of criminal behavior. The premise underlying his model was that offenders are rational beings who make decisions based upon such tangibles as wealth and the threat of punishment. The choices Ehrlich modeled deal with the mix of legal and illegal activities. His subsequent regression analysis of the variations in the levels of each index crime for each state in the U.S. failed to reject his hypothesis that the severity of the punishment (the length of the sentence) and the celerity of punishment (the joint probability of apprehension and imprisonment inversely affect the number of offenses.

Armed with Avi-Itzhak and Shinnar's model and Ehrlich's conclusions, Blumstein and Nagin developed a model to be used for analyzing imprisonment policy scenarios in a static environment. Their model is a non-linear program whose goal it is to minimize the level of crime, given that there exists an upper bound on the number of offenders who can be imprisoned; this capacity constraint is based upon an observation that the number of persons in prison in the U.S. has remained essentially constant since 1930. Although this constraint appears to hold nationally, on not so grand a scale, local or regional capacity could change with the demolition or construction of prison facilities. Thus, this model is best suited for macro analysis where the fixed-capacity constraint

probably is a very real limit.

Blumstein and Nagin concentrated on two policy variables: the probability of imprisonment given that an offender is convicted,  $Q$ , and the average time served in prison,  $S'$ . In addition, another variable which is the consequence of police and prosecutorial effectiveness (and higher-order policy variables related to budgetary processes) is the conditional probability of conviction given that a crime has been committed,  $q$ . The product of  $qQ$ , the conditional probability of imprisonment given the commission of a crime, times  $S$  results in  $qQS$ , the expected number of man-years of imprisonment per crime.

Blumstein and Nagin's expression for the aggregate crime rate is

$$C = \lambda \eta P, \quad (2-15)$$

where  $P$  is the fraction of the population that is criminal,  $\eta$  is the proportion of an offender's criminal career that he is active (not incarcerated), and the product  $\lambda \eta$  is the effective crime rate per offender. Both  $P$  and  $\eta$  were described as functions of  $Q$  and  $S$ . From Avi-Itzhak and Shinnar,

$$\eta(Q, S, \lambda q) = \frac{1}{1 + \lambda q QS}. \quad (2-16)$$

To include the deterrent effects of  $Q$  and  $S$  in the formulation of  $P$ , Blumstein and Nagin assumed the logistic function

$$P(Q, S) = \frac{e^{u(Q, S)}}{1 + e^{u(Q, S)}}, \quad (2-17)$$

where  $u(Q, S) = \gamma_0 + \gamma_1 Q + \gamma_2 Q S^n$  is the expected disutility of imprison-

ment for all offenders. Requiring for deterrence that  $\frac{\partial P}{\partial Q} < 0$  and  $\frac{\partial P}{\partial S} < 0$ , the following constraints on the logistic model's parameters were determined:

$$\gamma_1 < 0, \gamma_2 < 0, n > 0.$$

Models of this form have been used successfully in the past to describe in the aggregate decision processes similar to that examined here.

Blumstein and Nagin reported that the average number of persons incarcerated at any one time is

$$I = qQSC.$$

Since  $I \leq U$  where  $U$  is the upper bound on prison capacity, the final form of the model is,

$$\begin{aligned} \text{Minimize } C &= \lambda \eta(Q, S, \lambda q) P(Q, S) \\ \text{Subject to: } I &= qQS \lambda \eta(Q, S, \lambda q) P(Q, S) \leq U \\ 0 &\leq Q \leq Q_{\max} \leq 1 & (2-18) \\ 0 &< S \leq S_{\max} . \end{aligned}$$

Since both  $C$  and  $I$  are nonlinear, use of this model requires searching over the acceptable ranges of both  $Q$  and  $S$  so that  $C$  is minimized when  $I \leq U$ .

For a CJS with a fixed prison capacity, this model is another useful tool for assisting in the formulation of sentencing policy. The model does have several limitations which are inherent to analytical models and which were discussed for the previous model. In addition to

these limitations, one cannot help but question the formulation of  $P$ , the fraction of the population that is criminal. Specifically, it seems that the policy variable  $q$  should have been included in the offender's utility function since Ehrlich [27] found that  $P$  is inversely proportional to the product of  $Q$  and  $q$ . This change would allow additional experimentation on the deterrent effects of the CJS.

Another problem that detracts from this model as with the other analytical models is that the model is not dynamic; none of these models facilitates the exploration of transient behavior between two policies. A dynamic model would be especially desirable since the delays become extremely important when trying to optimize around a fixed capacity. The possibility of an infeasible level of incarceration (i.e.,  $I > U$ ) as the result of a policy change makes the examination of the dynamic response a critical shortcoming of this and its sister models.

## 2.2 Simulation Models of CJS Operations

Unlike the analytical models, the simulation models have emphasized the operations of the CJS as opposed to the characteristics of the offender population. By evaluating the effects that alternate parameter values have on some measure of performance, the simulation models have dealt with the issue of CJS policy directly. The analytical models, on the other hand, have been much more descriptive than prescriptive in character. The performance measures of the analytical models have been the crime rate while a few have used the expected number of re-arrests of the first offender. The performance measures of the simulation models, however, have varied considerably. As will be seen, the simulation models

have analyzed the CJS using one or more of the following as the objective criteria:

1. Cost
  - a. Annual CJS operating cost
  - b. Total CJS cost attributable to the average criminal career
2. CJS resource availability
3. Delays in processing offenders
4. Recidivism

#### 2.2.1 Queueing Models

The first serious attempt to model the operations of the CJS was developed by Navarro, Taylor and Cohen [54]. Their model, called COURTSIM, makes use of the General Purpose System Simulation (GPSS) language to trace on a day-to-day basis the paths along which offenders progress through the Washington, D.C. judicial system; COURTSIM is a model of steady-state behavior. The processing of an offender begins at the moment of his arrest but continues only to the point at which the presiding magistrate delivers his sentence. Unfortunate data deficiencies present at the time of the investigation precluded any detailed characterization of the offender while only that information deemed necessary to describe the offender flow was incorporated in the model. Incorporated into the model, however, was a limited number of such treatment-specific characteristics as the date of the indictment, the offender's bail status, the number of motions filed in court, the charge for the most serious crime committed, and the number of co-defendants in the trial.

Since the COURTSIM model was another product of the President's Commission on Law Enforcement and the Administration of Justice, one of its chief responsibilities was to successfully demonstrate the utility of simulation in dealing with strategic and tactical questions in criminal justice administration. The COURTSIM study is also particularly noteworthy for its treatment and analysis of court delays and the resulting backlogs that even today plague the judicial process. Besides including the unavoidable delays associated with processing the offender, capacity and resource scheduling constraints are introduced for each processing unit in order to incorporate these additional delay considerations into the model and, in so doing, to enhance the model's credibility.

Several experiments were conducted using the COURTSIM model to demonstrate the effects of various capacity and procedural changes on offender processing delay. Obviously, since the model's offender is so primitively described, only relativistic statements result from this analysis. While the authors themselves cautioned that their results were only tentative, their recommendations are worth noting. They recommended that improvements be made to data gathering capabilities so that the information required for such a model would be available for evaluation purposes, and they recommended that cost-effectiveness studies be conducted before CJS policy conclusions are drawn from the experiments on such models.

Fortunately for the simulation modeler tremendous progress has been made in the area of data collection; but, one severe limitation of simulation models has been their inability to simultaneously consider



resource availability constraints, resource or other operating costs as well as the queueing phenomena. A recent innovation in simulation systems, however, has shown that such limitations can be overcome in one simulation model. By developing a stochastic network model of the criminal court of Champaign County, Illinois, Hogg, DeVor and Luhr [38] demonstrated this capability using the Generalized Network Simulator, GNS. As the name implies, GNS simulates stochastic networks by considering the network nodes as either activities or events. The network's arcs exist merely to capture precedence relationships. Because of these attributes, GNS has been selected as the simulator for this research; its capabilities shall be described in more detail in Chapter IV.

As a result of the advanced data collection capabilities and of the advances in simulation software, the remaining shortcomings of Navarro, Taylor and Cohen's COURTSIM are not too restrictive. More recent court models, e.g., Holeman [39], are essentially applications of the methodology demonstrated with COURTSIM. Several of these models are discussed by Chaiken, et al. [19].

#### 2.2.2 A Continuous Flow Model

Comparing the COURTSIM model to the analytical models, COURTSIM does not consider the recidivism of offenders. Rather, the crime rate is translated into the offenders who are to be processed by the model, ignoring any distinction between recidivists and first offenders. This model is considered to be "open loop" in that recidivists are not modeled; the re-arrest of an offender is not simulated, nor is an offender's criminal career. Only the epoch during which an offender is under the direct purview of the CJS is simulated.

Another open loop model of CJS operations to have achieved acclaim by planners was first published in 1969 by Blumstein and Larson [12]. The so-called JUSSIM I model was used to forecast system costs, workloads, and resource requirements. Unlike the COURTSIM model, JUSSIM does not deal with individual offenders; consequently, queueing phenomena are not examined. Following their arrest, offenders are routed through the model by branching ratios that specify the proportion having a pre-defined characteristic that will follow a specific arc at each decision point in the system. The particular identifier used in JUSSIM's first application was the most serious crime for which the offender was charged. Any legitimate set of discriminators could, however, have been used to specify subsets of the arrested population. To forecast the workload, resource requirements and subsystem costs, the JUSSIM model is driven by a forecasting function of the total arrest rate. By following the flow of offenders through the model, administrators are able to predict the workload on each element in the model. Possessing this information it is a simple matter to compute the resources required for a given workload, the computation of the cost per resource unit following directly.

The beauty of the JUSSIM model lies in its ability to capture, if only in an elementary fashion, the essential characteristics of the CJS and to impute costs for handling alternate system loads which result from changes in operating policy. Of course, the approach is plagued with assumptions, but most of these can be dealt with with additional effort:

1. The fact that fixed and variable costs are both treated as

variable is a deficiency in the current model. Although Blumstein and Larson argue that fixed costs become variable in the long run, they fail to consider that certain expenses are contingent upon the construction or demolition of physical plant. Such costs should be considered fixed as to do otherwise is to assume a static physical plant.

2. Although the lack of delays in the model is at first appalling, for an open-loop model like JUSSIM I, their inclusion would have little effect on the resulting policy. According to the Presidential Task Force on Science and Technology [54] 80% of the cases filed in Washington, D.C. courts in 1965 took less than 28 weeks between arraignment and a trial disposition, the average delay being 15 weeks. Thus, although the delays in the model would range between three and seven months, the spillover of offenders arrested in one year and disposed of in the succeeding year should be approximately counterbalanced for any year; eliminating this spillover between years should cause only slight error in an unstable system and no error during a stable period.
3. Of Blumstein and Larson's assumptions, the one that is perhaps the most difficult to reconcile is the invariance of the branching ratios. Although significant trends, if they existed, were considered in developing these flow probabilities, the flow along one branch is not in any way related to the flow of another; nor is any thought given to relating the

branching ratios to the magnitude of the offender flow of a model component in order to incorporate a surrogate for the actual decisions being made in the component.

4. The final assumption that should be mentioned is the limited distinction between types of offenders. This assumption is more dependent upon the ingenuity of the modeler, the objectives of the study, and the accessibility of needed statistics than upon any deficiencies of the approach. Although the usual approach has been to differentiate between offender categories strictly on the basis of crime committed (cf., Blumstein and Larson [12], Cohen, et al. [20], CANJUS [11] [18] [40]), other offender descriptors such as race or sex or age could also be implemented with little difficulty.

#### 2.2.3 A Feedback Model of the CJS

In the same article in which JUSSIM I was first introduced, Blumstein and Larson [12] also described an extension which has extraordinary potential for criminal justice planning. The model, called JUSSIM II, is a feedback model wherein offenders are tracked from the point of their first arrest to the point where they finally leave the Criminal Justice System for the last time. JUSSIM II of necessity includes measures of criminal recidivism (the feedback process) in order to determine if and when offenders are re-arrested. The input to this model, unlike that for JUSSIM I, is the number of persons during each year who are arrested for the first time in their lives. The number of first offenders is then added to the number of recidivists to give the total number of arrestees during the year.

The flow of offenders is treated similarly to the flow in JUSSIM I except that each crime-specific flow variable is now further broken down by offender age. The first offenders and, of course, the recidivists are additionally described by the age of their initial arrest in order to be able to compute such criminal career-related statistics as the number and type of crimes for which the offender is charged. The subsystem cost estimates developed using JUSSIM I are then used to approximate the average CJS processing cost attributable to each offender over his entire criminal career. Consequently, with a realistic version of JUSSIM II criminal justice planners can analyze the implications of various programs designed to reduce recidivism vis-a-vis the offender's criminal career profile as well as the CJS operating cost, a powerful approach indeed for measuring and testing the effectiveness of alternate policy scenarios.

The manner in which Blumstein and Larson formulated the offender flow in JUSSIM II is well worth examining. The model's input consists of the number of first offenders grouped by age and by offense. The model then combines this virgin arrestee flow, (which may be either an age-specific cohort or the entire first offender population, with the recidivist component. Then, the model determines by means of branching ratios the path along which each offender travels through the CJS. (Remember, no delays are considered up to this point.) As this published version of JUSSIM II is a highly simplified model, only five criminal dispositions were included:

1. Juvenile care
2. Release without charge

3. Acquittal
4. Probation
5. Incarceration

If the offender is incarcerated, JUSSIM II would determine the delay until the inmate is to be released and whether or not he is reincarcerated for a parole violation. For each disposition, the model computes the number of arrestees who are again arrested. The re-arrest probability  $P(a)$  was assumed to be a piece-wise linear function of an offender's age,  $a$ .

After determining the number of re-arrested offenders using  $P(a)$ , an estimate of the time between an offender's release from the CJS and his subsequent re-arrest is determined. A negative exponential distribution is assumed and the average delay time over all dispositions is determined to be approximately two years. Using the method of moments to estimate the parameters of the delay, the density function is

$$P(\text{delay} = x \text{ years}) = \frac{1}{2} e^{-x/2}.$$

When an offender is re-arrested, JUSSIM II determines the most serious crime for which he is charged by invoking the Markovian assumption: the current offense depends solely upon the type of the immediately preceding crime. Wolfgang, Figlio and Sellin [80] tested this assumption with their male birth cohort and found this model to be an acceptable representation of crime switching behavior. In addition, Blumstein and Larson examined several cases having different so-called "crime switch" transition matrices. They found that the number of career arrests

for each index crime is more sensitive to the arrest and re-arrest probabilities than to the crime-switch phenomenon.

The assumptions which are invoked for the recidivism component of the JUSSIM model are:

1. The probability of recidivism is only a function of an offender's age, his most recent crime, and the disposition of the CJS following his latest arrest;
2. Crime switching behavior depends solely on the offender's previous crime;
3. The delay between an offender's release from the CJS and his subsequent re-arrest is assumed to be a distributed negative exponential, the mean being a function of the CJS disposition.

Since the JUSSIM II analysis of career criminal cost is dependent upon the cost estimates derived using JUSSIM I, many of the limitations of the open-loop model also apply to the feedback model.

Because of the power of the feedback model, several implementations of JUSSIM II exist today. Among these, the Canadian model CANJUS [11] [18] [40] and implementations of JUSSIM in Pittsburgh and Philadelphia [20] are most noteworthy. In addition, Mathematica's PHILJIM model represents an extension of the JUSSIM II concept [19]. The carryover of offenders into a succeeding year because of CJS delays is handled explicitly, thereby removing some of the prediction errors caused by not including such delays in the model. PHILJIM has been implemented in Alaska, Denver, Sacramento, Austin, and Washington, D.C.

#### 2.2.4 A Feedback Model of Corrections

Another feedback model of CJS operations was developed by Pittman [50] to evaluate alternatives in connections policy. His model is a Markov chain representation similar to the model of crime-switching behavior used in JUSSIM II. Unlike the crime-switch model which possesses states corresponding to the seven index crimes, Pittman's offenders may be in any of the following four states:

1. In prison because of conviction,
2. In prison because of a technical violation of parole,
3. On parole,
4. Free but not under CJS supervision.

The matrix  $P$  is composed of elements  $p_{ij}$ , the steady-state transition probabilities from state  $i$  to state  $j$ , where  $i=1,2,3,4$  and  $j=1,2,3,4$ .

The approximate cost  $c_{ii}$  of being in each state for one year was empirically determined; however, since each offender may be in either one or two states during the year, the cost  $c_{ij}$  for  $i \neq j$  was assumed to be

$$c_{ij} = (c_{ii} + c_{jj})/2 + k_{ij},$$

where the cost of the transition between states is  $k_{ij}$ . Thus, the offender is assumed to spend half of a year in each state.

Possessing the transition matrix  $P$  and the cost matrix  $C$ , Pittman was able to estimate future system loads and the crime mix given the number of first offenders who are arrested and convicted. In addition,



by simulating a number of years,  $N$ , Pittman was also able to determine the expected number of times the offender is re-arrested,

$$E(r) = \sum_{m=1}^N P_{41}^m .$$

During steady-state, the average time that an offender is in any state is determined analytically by

$$t_i = (1 - p_{ii})^{-1} .$$

Pittman used this identity to compute the average sentence length,  $t_1$ . Also using these last two relationships, Pittman was able to determine the expected criminal profile; by also making use of the cost matrix  $C$ , he was able to compute the expected career criminal cost of an offender.

Although Pittman's model is obviously more analytical than similar; his emphasis is on the issues which actually change the flow of offenders within the corrections subsystem. Unlike the models of Belkin et al. [9], Avi-Itzhak and Shinnar [5], and Blumstein and Nagin [14], Pittman's model can analyze the effects on the offender profile of changing the transition probabilities  $p_{ij}$ . In addition, by changing the costs  $c_{ij}$ , this model can also be used to develop a least-cost solution for reducing crime and thereby overcome one of the major deficiencies with the previous analytical works.

Of course, the criticisms of Blumstein and Larson's model (Section 2.2.2) apply here as well. The time invariance of the transition probabilities could be a problem in forecasting system load; if the  $p_{ij}$  do change, the calculations for  $E(r)$  and for  $t_i$  also change. Aggregating

the costs can also create problems if the future cost distribution changes because of new facilities or programs. Further disaggregation of the variables which describe the offender would make Pittman's model more meaningful but also more complex. For example, to include the seven index crimes would increase the data requirements seven-fold. To further expand the scope of the model to include the police and court subsystems expands the data requirements and complicates the computation of the performance measures. Thus, to resolve the limitations of Pittman's model, would require considerably more data and model analysis in order to draw conclusions about the performance of the entire CJS. Since steady-state analysis is not as useful as simulated analysis for such complex systems, Pittman's approach is more useful in subsystem analyses than it is for global CJS studies.

#### 2.2.5 A Feedback Queueing Model of the CJS

In 1972, a queueing model was developed of the entire CJS which incorporated a model of offender recidivism similar to that demonstrated by Blumstein and Larson. The model is called DOTSIM, an acronym for Dynamic Offender Tracking Simulation [19]. DOTSIM like COURTSIM follows each offender through the Criminal Justice System; however, like JUSSIM II the input to the DOTSIM model is the number of first-offense arrests by crime type. Each offender's attributes are randomly generated upon his first arrest.

DOTSIM has the capability of delaying the processing of offenders whenever the demand for a particular resource exceeds its supply. This competition over scarce resources makes DOTSIM a keen tool for CJS analysis since a particular policy alternative may arise which

could cause resource shortages to delay offenders longer than expected. This characteristic, in the view of this author, although contrary to the conclusion espoused by Chaiken, et al. [19], makes the DOTSIM approach superior to the JUSSIM II model and even to the PHILJIM model with its surrogate delay capability. The random processing of offenders through the CJS itself lends greater resolution to the intricacies of offender-specific policy formulation. The effects of each policy scenario can be ascertained by measuring the change in the crime rate, resource requirements and system costs relative to a base-line policy.

The costs embedded in the model include those which are directly attributable to an offender based upon his usage of resources. The indirect costs of equipment and facilities were also apportioned to the offenders based upon their percentage utilization over an entire year.

The DOTSIM model does, however, have its limitations. First, the increased cost of operating the model and of collecting the necessary empirical data restricts its usefulness as a research tool. This ostensibly is the reason that it has been never used for policy analysis [19]. In addition, the model was formulated in such a way as to prevent the testing of specific policies which examine differential recidivism tendencies of alternate correctional programs; DOTSIM's recidivism model was aggregated over all dispositions. A final criticism of this model is its inability to determine the average career criminal cost, a useful performance measure for evaluating CJS policy.

### 2.3 Summary

The CJS models used for evaluation purposes have been of two types: analytical and similar. The analytical models have all been aggregate models of homogeneous offender populations, whereas the simulation models have generally disaggregated the offender population along offense categories. All of the simulation models have included cost as a factor in their analysis; none of the analytical models, however, have evaluated the cost of alternate scenarios. In fact, two policy-oriented analytical models developed by Avi-Itzhak, et al. and Blumstein and Nagin concentrate primarily on the crime rate, the former through the reduction of recidivism and the latter through the reduction of crime perpetrated both by first offenders and by recidivists. Blumstein and Nagin also examine the crime reduction issue under the influence of an upper bound on prison resources.

Historically, the simulation models have proven more flexible than their analytical counterparts. The simulation model JUSSIM II for example, uses both costs and resources as performance criteria in addition to being able to examine criminal recidivism. Thus, although both types of models have been used to address the issues of recidivism and resource constraints, the simulation model with its costing element simultaneously embedded in the same construct becomes a superior tool for analysis. By overlaying the additional features of a discrete event simulation model like DOTSIM (Dynamic Offender Transaction Simulation) or like the Generalized Network Simulator (GNS), the simulation approach to CJS analysis is as sophisticated a tool for holistic analysis as

might ever be required by modelers or policy analysts. Such a model could be either as aggregate or as detailed as the analyst desires. For example, in modeling plea bargaining in a holistic model, the queueing behavior of the CJS could be constrained by resource limits and the costs of processing an offender could be determined for each stage in the model. The plea bargaining component itself, could also be as complicated as necessary, since the model would not be bound by mathematical tractability. The only restrictions on such a model would be, then, essentially empirical. Can the required data be collected, and can the model and its output be validated? Because of the advance in the collection and dissemination of information, however, such simulation models are feasible.

The proposed simulation model should possess the majority of the characteristics of its predecessors which are listed in Table 1.

Table 1. Capabilities of Models of the CJS

MODEL (Year)	Model Type #	Model Purpose*	Performance Measures							Model Characteristics								
			Total Cost	Career Criminal Cost	Crime Rate	Recidivism	Deterrence	Delay	Resources	Costs	Deterrence	Recidivism	Recidivism by Disposition	Incapacitation	Queues	Resources	Offender Demographics	Crime Switch
Christensen (1967)	A	P			X	X		X				X		X				
Belkin, Blumstein and Glass (1973)	A	D										X						
Avi-Itzhak and Shinnar (1977)	A	B			X	X						X		X				
Blumstein and Nagin (1977)	A	B			X	X	X		X		X		X					
Navarro, Taylor and Cohen (1967)																		
COURTSIM	S	B	X					X	X	X					X	X		X
Blumstein and Larson (1969)																		
JUSSIM I	S	B	X						X	X						X		
JUSSIM II	S	B	X		X	X			X	X		X	X	X		X	X	X
Pittman (1973)	S	B	X	X				X		X		X	X	X			X	
DOTSIM (1972)	S	B	X					X	X	X		X		X	X	X		X

\* Note, primary model purpose is either D = descriptive, P = predictive, or B = prescriptive (policy analysis)

# Model Types are A = analytical, S = simulation

## CHAPTER III

### ECONOMICS OF THE COURTS

#### 3.0 Introduction

As pointed out in the first chapter, the prosecutor has played an ever-increasing role in the adjudication process of the courts. Before the institutionalization of plea bargaining, the courts alone determined the guilt of a defendant and sentenced those in need of correction; however, the ever-increasing burden on the courts has increased the importance of the prosecutor. In response to the massive court caseloads, the prosecutor now assists in the disposition of cases himself by allowing defendants to negotiate guilty pleas which result in less severe charges. This process is loosely called "plea bargaining."

Because of the interest during the past decade to better understand crime and its control, economists have begun to develop models which structure the plea bargaining process in an attempt to explain how it works. (Thus, the economic models of the courts are descriptive models, using the terminology of the proceeding chapter.) Because these models have not been used for quantitative policy analysis, the incorporation of the plea bargaining mechanisms as described by economists into a simulation model like GNS or DOTSIM should prove to be useful for CJS policy evaluations. To facilitate the development of a plea bargaining component in a discrete event simulation model, in Section 3.2 and 3.3 the economic interpretations of the interaction

between an offender and the prosecutor are discussed. Then in Section 3.3, by building upon these two efforts, a more extensive model is postulated which predicts the effect of certain case-specific information on the outcome of plea negotiations. Specifically, the severity of an offender's crime and an offender's arrest record are incorporated into the prosecutor's decision function and the effect on the outcome of plea bargaining is postulated.

The analysis of the preceeding models follows immediately. The equations and dynamics of each model are described in order to clarify the assumptions of the plea bargaining component of the simulation model developed for this research.

### 3.1 A Pareto Optimal Model

The economist who pioneered in the description of the criminal court was William Landes. This man developed a theoretical model "that identifies the variables relevant to the choice between a settlement and a trial" [43; p. 165]. According to Rhodes, he demonstrated "that the plea bargaining process ... can be characterized as a 'market' in which the prosecutor 'buys' guilty plea convictions in exchange for promises of sentencing leniency" [57; p. 1]. Landes's model, it turns out, is an individually tailored compromise between the defendant and the prosecutor, with each participant expecting to gain from the outcome of plea negotiations. This view results in a Pareto optimal solution for both the prosecutor and the defendant.

#### 3.1.1 Model Equations

To reach a final decision in the bargaining process, each



participant attempts to maximize his objective function subject to the availability and productivity of his resources. Specifically, the prosecutor tries to maximize the expected sentence length of all offenders,

$$E(S) = \sum_{i=1}^m P_i S_i \quad (3-1)$$

where  $E(S)$  is the expected sentence duration of all defendants,  $m$  is the number of defendants to be prosecuted,  $P_i$  is the probability of convicting defendant  $i$ , and  $S_i$  is the length of the  $i^{\text{th}}$  defendant's sentence. The prosecutor's budget constraint may be written as

$$\sum_{i=1}^m C_i X_i = B \quad (3-2)$$

where  $C_i$  is the cost of prosecuting the  $i^{\text{th}}$  defendant,  $X_i$  is 1 if the defendant is prosecuted and zero otherwise, and  $B$  is the budget available to the prosecutor during the planning horizon.

Each defendant wishes to influence the final outcome of plea bargaining. According to Landes, this is equivalent to his maximizing the expected utility of going to trial,

$$E(Z_i) = P_i^* U_i(W_i) + (1-P_i^*) U_i(W_i^d) \quad , \quad (3-3)$$

where  $E(Z_i)$  is the expected utility of a trial of defendant  $i$ ,  $P_i^*$  is the defendant's estimate of the probability of his conviction if he goes to trial,  $U_i(W_i)$  is the defendant's utility for a conviction, and  $U_i(W_i^d)$  is the defendant's utility for dismissal.

The variable  $W_i$ , the endowment from a trial conviction, is a function  $f$  of the defendant's wealth prior to arrest,  $Y_i$ , the expected length of his sentence,  $S_i^*$ , and the value of the resources that he expends for his defense,  $R_i$ . That is,

$$W_i = f(Y_i, - S_i^*, - R_i).$$

The variable  $W_i^d$ , on the other hand, is his endowment from being dismissed. It is written as a function  $g$  of  $Y_i$  and  $R_i$  according to

$$W_i^d = g(Y_i, - R_i).$$

Both  $f$  and  $g$  are increasing functions of their arguments.

By defining

$$W_i' = f(Y_i, - S_i', - R_i)$$

as the endowment from a conviction with the negotiated sentence  $S_i'$ ,

Landes assumes that a non-trial settlement occurs whenever

$$\pi_i = U_i(W_i') - E(Z_i) > 0 \quad . \quad (3-4)$$

Thus, the decision to schedule a trial for a defendant (viz, not allow a guilty plea) depends upon:

1. The prosecutor's and the defendant's estimates of the probability of conviction by trial ( $P_i$  and  $P_i^*$ , respectively);
2. The defendant's attitude toward risk (as it is embodied in his utility function  $U_i$ );
3. The severity of the offense (as it affects  $S_i$ );

4. The cost differentials incurred by both defendant and prosecutor for the trial versus the negotiated plea outcomes;
5. The defendant's budget and the prosecutor's budget.

The case that is most likely to be settled out of court by a negotiated plea, then, occurs whenever "the prosecutor and suspect agree on the expected outcome of a trial, the costs of a trial to both parties exceed their settlement costs, and suspects are generally risk averse in their trial versus settlement choice" [57; p. 173].

### 3.1.2 Model Dynamics

Using his model as a vehicle for analysis, Landes claims that offenders with greater financial resources are more likely to plead to a lower negotiated sentence than offenders without financial resources. This conclusion is based upon the premise that such a defendant is better able to expend more resources to influence this outcome. In as much as the longer sentence represents foregone opportunities to the defendant, he will spend more to reduce the maximum possible sentence. Thus, the wealthier the defendant, the greater the charge reduction expected. (This model does not, of course, consider the potential notoriety bestowed on the prosecutor for bringing a particularly well-known or wealthy defendant to trial.)

Landes also claims that a backlog of trial cases serves to ration the limited supply of court trials. When a backlog develops because, for example, the length of a trial increases, additional resources are required to prosecute a defendant enroute to a trial. In addition, the extra delay effectively reduces the number of high  $S_i$  convictions by

those cases delayed beyond the planning horizon. The effect of the increased backlog is that the prosecutor must increase the number of negotiated pleas in order to counteract the reduction in  $E(S)$ . Eventually, an equilibrium backlog is regained with a larger percentage of the total number of cases being negotiated than before the increase in the backlog.

### 3.1.3 Summary

Landes's model of plea bargaining subsumes the notion of what may be called personalized justice: the prosecutor investigates each defendant in order to estimate the expected sentence of the defendant,  $P_i S_i$ . Then, the implication is that through careful negotiations, the prosecutor and defendant agree to either conduct a trial or to have the defendant plead guilty to a lesser charge. Each participant's ability to negotiate is based upon his budget, upon his estimates of the parameters under consideration, and upon his willingness to pay the price for the desired outcome. The result of plea bargaining is said to be Pareto optimal in that each participant expects to benefit from the outcome of these negotiations.

## 3.2 A Resource Constrained Model

Like his predecessor Landes, Rhodes [57] developed a theoretical economic description of the mechanics of plea bargaining. By altering certain assumptions regulating the behaviors of the defendant and the prosecutor, he de-emphasized the importance of the negotiations between these participants. Implicit in the Landes model is the assumption that the prosecutor has sufficient valid information concerning each defen-

dant to judiciously allocate his resources between cases which compete for his fixed budget. Rhodes, however, does not assume this. His position is that the prosecutor's budget constraint severely restricts his ability to investigate his oversized caseload. He explained,

Because of the budgetary constraints imposed upon the prosecutors and others, the processing of defendants, including plea bargaining dispositions, may not be as individualized as was assumed in the Landes model. Since the prosecutor does not have the resources for detailed investigation of every suspect's case, routine concessions rather than rigorous barter are the normative pattern of reaching compromise. [57; pp. 16-17]

### 3.2.1 Model Equations

In characterizing his views of a considerably less personal form of justice, Rhodes describes the defendant as wanting to minimize a utility function composed of the expected reduction in his sentence and of his total consumption of goods and services while not being held by the CJS. This description of the defendant is similar to that proposed by Landes with the following exception. Rhodes explicitly constrains the defendant's expenditures for his own defense by

$$C_{fi} + C_{di} = D_i \quad (3-5)$$

where  $D_i$  is the budget of defendant  $i$ ,  $C_{fi}$  is the cost of defendant's consumption while free, and  $C_{di}$  is the defendant's expenditure for his own defense.

Rhodes also portrays the prosecutor as maximizing a function  $\pi$ . Reformulating his model so that it corresponds more closely with equations 3-1 and 3-2,

$$\pi = \sum_{i \in I} P_i S_i + p E_p \quad (3-6)$$

where  $I$  is the set of defendants who are sent to trial,  $p$  is the number of offenders who plead guilty during the planning period,  $E_p$  is the expected sentence for the defendant who pleads guilty, and  $P_i$ ,  $S_i$  and  $m$  are defined as in equation 3-1. He formulates the prosecutor's budget constraint such that the allocation of resources to cases is much more structured than according to the Landes model. For offenders who go to trial, Rhodes assumes that the cost to the prosecutor is fixed at  $C_T$ , whereas for those offenders who plead guilty the cost is also fixed but at an amount  $C_p < C_T$ . Thus, the prosecutor's budget constraint is written as

$$\sum_{i=1}^m X_{1i} C_p + \sum_{i=1}^m X_{2i} C_T = B \quad (3-7)$$

where  $X_{1i}$  is 1 if defendant  $i$  pleads guilty and zero otherwise,  $X_{2i}$  is 1 if the defendant goes to trial and zero if he does not, and  $B$  is the prosecutor's budget. Furthermore, the constraints

$$\sum_{i=1}^m X_{1i} = p \quad (3-8)$$

$$\sum_{i=1}^m X_{2i} = n$$

define the number of offenders who pleads guilty and who go to trial, respectively, where  $m \geq n + p$ . The number of offenders who are released prior to their arraignment is the difference

$$r = m - (n + p)$$

With this formulation of his budget constraint, the prosecutor

must determine the optimal couplet  $\{X_{1i}, X_{2i}\}$  for each offender  $i$ . Accordingly, the prosecutor first determines the parameters  $n$ ,  $p$  and  $r$  and he then determines which offenders  $i$  are to be prosecuted and how a conviction might be obtained. Thus, viewing this as a sequential two-stage decision process, the prosecutor must first select the offenders to be prosecuted, either releasing or disposing informally of all others. Second, he "must determine and offer plea bargaining sentences of sufficient leniency to maintain an orderly flow of cases through the criminal courts" [57; p. 21].

In his study of the dynamics of plea bargaining, Rhodes discusses two cases which characterize different assumptions about the amount of a priori information available to the prosecutor on each defendant. For Case I, the prosecutor has complete information whereas for Case II the prosecutor does not have adequate information describing either the defendant or the crime until after the first decision has been made. In either case, the prosecutor is assumed to have accumulated sufficient information on each defendant prior to his deciding whether to try a particular case in court or to offer a reduced charge in exchange for a guilty plea.

### 3.2.2 Case I Dynamics

For Case I, the prosecutor has sufficient information on each offender prior to selecting those to be prosecuted. He ranks the defendants by his estimate of their convictability,  $\phi_i$ . An offender's convictability is defined as the probability of his being convicted for having committed the charged offense, but it excludes any effect that the defendant's resource expenditures ultimately have upon the proba-

bility of conviction. Thus, an offender's convictability is composed of the following factors:

1. His age, race and sex,
2. His criminal history,
3. The characteristics of the present offense,
4. The amount and quality of the evidence against him,
5. The prosecutor's expenditure on the case,
6. The time required to dispose of the case.

From this ranking of defendants, the high  $\phi_i$  criminals are those who are almost certain to plead guilty to lesser charges in order to avoid the expenses and potentially harsher sentences of a trial. The low  $\phi_i$  offenders, on the other hand, are certain to be released if the prosecutor's budget would otherwise be exceeded. Those defendants whose  $\phi_i$  appears in the middle portion of the convictability continuum, however, may either be sent to a trial or they may negotiate a guilty plea. If the system is in equilibrium, it is clear that the high  $\phi_i$  defendants would plead guilty, whereas the lower  $\phi_i$  defendants who are not released will go to trial. Thus, the prosecutor can quite easily determine  $r$ ,  $n$  and  $p$  using historical values of  $C_T$ ,  $C_p$ ,  $B$  and  $M$  when the system is in steady state.

When the system is not in steady state, however, the determination of  $X_{1i}$  and  $X_{2i}$  becomes less clear. When a defendant first enters the jurisdiction of the prosecutor, his convictability is evaluated and his position on the  $\phi_i$  continuum is resolved. The first question that the prosecutor must address is should the offender be released? This decision, according to Rhodes, is merely an economic one. If the



defendant's  $\phi_i$  falls below some threshold value (determined so that  $pC_p + nC_T = B$ ), then he is to be released. For the prosecutor's second decision, the criteria for sending the remaining defendants to a trial or allowing them to negotiate a guilty plea is less precise. Obviously, those defendants whose  $\phi_i$  is very low will go to trial and those whose  $\phi_i$  is high will negotiate guilty pleas. However, for those defendant's whose  $\phi_i$  is near the critical point, Rhodes assumes that these offenders may be forced into either alternative, depending on several other factors. The factors which Rhodes explores are:

1. An external increase in the prosecutor's budget (that is, from  $B$  to  $B'$ ),
2. An external increase in the defendant's budget (viz, from  $D_i$  to  $D'_i$ ), and
3. An increase in the delay an offender experiences while awaiting a trial.

Because Rhodes's analysis of the effects of an increase in the defendant's budget was inconclusive, this particular factor shall not be explored further.

An increase in the prosecutor's budget from  $B$  to  $B'$ , assuming  $C_T$  and  $C_p$  remain unchanged, increases the number of offenders prosecuted ( $n' + p' > n + p$ ), it reduces the number of guilty pleas ( $p' < p$ ), and it increases the number of trials ( $n' > n$ ). These conclusions are based upon the assumptions that the probability of conviction at a trial decreases as the number of trials increases,

$$\frac{\partial P_i}{\partial n} < 0,$$

and that the following condition holds,

$$\xi_i = \frac{\partial P_i}{\partial p} + p \left( \frac{\partial^2 P_i}{\partial p^2} \right) < 0.$$

Under these assumptions, Rhodes demonstrates that the following are true:

$$\frac{\partial n}{\partial B} = - \left[ \frac{\partial P_i}{\partial n} (C_T - C_p) + \xi_i C_T \right] > 0$$

$$\frac{\partial p}{\partial B} = \frac{\partial P_i}{\partial n} (C_T - C_p) < 0 \quad (3-9)$$

$$\frac{\partial (n+p)}{\partial B} = -\xi_i C_T > 0.$$

The length of the pre-trial delay at time  $t$ ,  $d_t$ , affects the prosecutor's disposition of offenders. Rhodes showed that if

$$\zeta_i = \frac{\partial P_i}{\partial d_t} + p \left( \frac{\partial^2 P_i}{\partial p \partial d_t} \right),$$

then the effect of the pre-trial delay on the variables  $n$ ,  $p$  and  $r$  is:

$$\frac{\partial p}{\partial d_t} = \frac{\zeta_i C_T^2 - \left( \frac{\partial P_i}{\partial d_t} \right) C_T C_p}{-(C_T - C_p)^2 \frac{\partial P_i}{\partial n} - \xi_i C_T} < 0$$

$$\frac{\partial n}{\partial d_t} = - \left( \frac{C_p}{C_T} \right) \frac{\partial p}{\partial d_t} > 0,$$

$$\frac{\partial(n+p)}{\partial d_t} = \frac{\partial n}{\partial d_t} + \frac{\partial p}{\partial d_t} = \left(1 - \frac{c_p}{c_T}\right) \frac{\partial p}{\partial d_t} < 0.$$

For this to be true, the probability of conviction is assumed to decrease as  $d_t$  gets large:

$$\frac{\partial p_i}{\partial d_t} < 0,$$

$$\frac{\partial^2 p_i}{\partial p \partial d_t} < 0.$$

### 3.2.3 Case II Dynamics

For the second case that Rhodes describes, the prosecutor does not have any information on the defendants prior to selecting those to be prosecuted. Accordingly, the prosecutor randomly chooses the  $r$  defendants to be released or informally treated. The remaining  $(n+p)$  offenders are once again ranked by their  $\phi_i$  in order to separate those to be sent to trial from those who will negotiate a plea. The dynamics of this second case are in every respect identical to the dynamics displayed by Case I, with one exception. When a prosecutor's budget is increased, the number prosecuted will likewise increase; however, because the offenders are chosen randomly, the prosecutor is likely to prosecute an offender whose  $\phi_i$  is significantly lower than the threshold which dictates that he be sent to trial. Therefore, rather than a concomitant decline in the number of guilty pleas, the number of offenders sent to trial as well as the number who plead guilty both increase. Rhodes shows that

$$\frac{\partial n}{\partial B} = \frac{\partial p}{\partial B} .$$

#### 3.2.4 Summary

The Rhodes model describes plea bargaining as being a highly constrained, two-stage decision process in which the defendant actually influences the prosecutor's decisions very little. For the first decision stage, the prosecutor must separate the offenders into two groups. On the first group of offenders, he spends a negligible amount of time and resources per case to determine that pursuing the case further would ultimately result in a dismissal. On the second group, he intends to prosecute each case until either a court disposition or a guilty plea is extracted. For this latter group of cases, Rhodes assumes that the prosecutor spends a fixed amount on the defendants who plead guilty and a smaller fixed amount on those who go to trial. Thus, for his second decision he must promise the same sentencing leniency for each guilty plea because no one case is singled out for special consideration (i.e., extra resource expenditures). Of those offenders who do not plead guilty, they are given a court trial where a harsher sentence is expected upon conviction.

Rhodes analyzes the dynamics of plea bargaining by postulating a convictability function which determines the true and known value of the likelihood of a defendant's being convicted prior to his expending time and money for his defense. For the two scenarios that Rhodes analyzes, the convictability of each defendant is assumed to be available for both decisions in Case II while it is available only for the second decision in Case I. The signs of the partial derivatives of

the number of offenders who are prosecuted, who plead guilty, and who go to trial with respect to changes in the prosecutor's budget and to changes in the pre-trial delay are summarized in Table 2 for each situation.

Table 2. The Effects on Plea Bargaining of Changes in the CJS

Changes in the CJS  Prosecutor's Disposition	Increase Prosecutor's Budget, B		Increase Pre-Trial Delay, $d_t$	
	Case 1	Case 2	Case 1	Case 2
Number of Offenders Prosecuted ( $n+p$ )	+	+	-	-
Number of Offenders Sent to Trial ( $n$ )	+	+	+	+
Number of Offenders Who Plead Guilty ( $p$ )	-	+	-	-

Note: A "+" indicates the change causes an increase in the number of occurrences of the corresponding event; a "-" implies a reduction.

### 3.3 A Career Criminal Model

Of the two economic models of plea bargaining developed by Landes and Rhodes, the mechanisms described by Rhodes are more readily implemented in a digital simulation like that proposed for this research. In addition, the model proposed by Landes does not address the issue of defendant release (Rhodes's first decision point) and thereby ignores part of the structure of plea bargaining that would otherwise enrich such a simulation model. The two-stage decision structure also lends itself readily to the actual structure of the CJS. The prosecutor's first decision (to release the defendant) may be exercised either before, after, or both before and after the grand jury hearing; his second decision would actually occur prior to the arraignment hearing, but would not affect the flows of defendants until immediately following this hearing. (See Chapter IV, Section 4.2.) Because of the superiority of the Rhodes model in this context, it is used as the basis for the plea bargaining component of the simulation model developed for this thesis. Its implementation is discussed along with the other aspects of the simulation model in Section 4.2 of Chapter IV.

Although the model itself does not have any severe shortcomings, Rhodes's analysis of the model was restricted. Although he examined the dynamics of plea bargaining under several conditions, he failed to describe the effects of several case-specific factors which influence both of the prosecutor's decisions. The reason for this apparent oversight is that Rhodes chose to analyze those factors which affect the outcome

of plea bargaining, but which are exogenous inputs to the plea bargaining model. From this perspective, he aggregated several case-specific factors which would otherwise directly affect the prosecutor's estimate of a defendant's convictability under the heading of a priori information.

It is the objective of this section to postulate the dynamics of two factors which affect a particular case's outcome, the severity of the current crime and the total number of times a defendant has been arrested. (The severity of an offense might be determined, for example, by using Sellin and Wolfgang's crime seriousness scale [60].) Incorporating these two bits of information in the defendant's convictability function  $\phi_i$ , the mechanics of Rhodes's model is augmented by the individuality of each case. Furthermore, the resulting simulation model allows case-specific issues which otherwise would be lost in an aggregate model to be explored using digital simulation. By selecting the defendant's criminal history as one of these informational variables, the impact of the career criminal in resource constrained environments can explicitly be experimented with using such a simular model.

### 3.3.1 Model Equations

The equations which describe this model of plea bargaining have not changed from Rhodes's formulation. Only the model dynamics has changed by postulating the relationship of case-specific information to the outcomes of this process.

### 3.3.2 Model Dynamics

In discussing the dynamics of plea bargaining when case-specific

information is available to the prosecutor, the distinction is maintained between Case I when a priori information is available and Case II when it is not. Under the scenario of Case II, the no a priori information rule prevents the prosecutor from knowing before his first decision either the severity of the present offense or the offender's criminal history; however, both pieces of information become available to him prior to his first decision for Case I and following the first decision for Case II.

For this analysis, it shall be assumed that the cost of acquiring crime-specific knowledge does not directly impact the prosecutor's budget. It is further assumed that the police in their investigations determine the severity,  $s_i$ , of each offender's crime and that they transmit it to the prosecutor at no additional cost to either. For the determination of the number of offenses an offender has already committed, the cost of maintaining the information retrieval system necessary to store such data is assumed to be covered by grants from other CJS agencies which then make it available at no extra cost to the prosecutor. Thus, for either bit of information to be available to the prosecutor,  $C_T$  and  $C_P$  are not increased and any effect on the disposition of a defendant is the unconfounded effect of the case-specific information on  $\phi_i$ .

When the severity of each offense is available to the prosecutor, the convictability of defendant  $i$  is assumed to vary as

$$\frac{\partial \phi_i}{\partial s_i} > 0.$$



From the earlier discussion of Rhodes's model, an offender's preference for a guilty plea increases as  $\phi_i$  increases. Thus, for a homogeneous offender population whose distribution of offense severity scores is symmetric with constant mean  $\bar{s}$ , an offender with  $s_i > \bar{s}$  is more likely to plead guilty than an offender with  $s_i \leq \bar{s}$ , all other factors being equal. When  $s_i$  is also available prior to the prosecutor's first decision, the prosecutor is more likely to release those offenders whose  $s_i < \bar{s}$  than those whose  $s_i > \bar{s}$ . These results are displayed in Table 3.

Table 3. The Effects of Case-Specific Information on Plea Bargaining

Case-Specific Information  Prosecutor's Disposition	Above Average Crime Severity		Above Average Number of Pre- vious Arrests	
	Case 1	Case 2	Case 1	Case 2
Probability Offender i is Prosecuted	+	0	+	0
Probability Offender i goes to Trial	-	-	-	-
Probability Offender i Pleads Guilty	+	+	+	+

Note: A "+" indicates the information increases the likelihood of a disposition; "0" indicates case-specific information is not available; "-" implies a reduction in the likelihood of a disposition.

The assumptions regarding the homogeneity of the offender population and the symmetry of the  $s_i$  distribution are very important to this analysis. In essence, they enable the analysis of case-specific information unencumbered by the phenomena which Rhodes evaluated. If these assumptions had not been made, the factors  $\frac{\partial P_i}{\partial n}$ ,  $\xi_i$  and  $\zeta_i$  defined earlier would impact how the prosecutor relates to changes in an individual offender's  $s_i$ . However, since these assumptions have been made, such effects can safely be ignored.

If the criminal history of each offender is available to the prosecutor instead of the severity of an offense, the convictability of an offender is also directly affected by the number of times  $a_i$  that he has already been arrested,

$$\frac{\partial \phi_i}{\partial a_i} > 0.$$

For the same reason as described when  $s_i$  is available, if an offender shows a greater than normal propensity to recidivate (as demonstrated by  $a_i$ ), then he is also more inclined to negotiate a guilty plea in order to guarantee for himself a smaller sentence. Similarly, if  $a_i$  is greater than the average recidivism of an offender  $\bar{a}$ , the offender is more likely to be prosecuted than not, assuming all other factors remain constant. For reasons stated earlier, the distribution of the random variable  $a_i$  is also assumed to be symmetric while the offender population is assumed homogeneous.

The results of the prosecutor's knowing the  $a_i$  for each offender is summarized in Table 3.

### 3.4 Summary

Repeating the objective of this chapter, it was desired to show that the economic interpretation of plea bargaining presents a viable description of an otherwise untenable process. The treatment in this chapter has examined two opposing economic views of this process. The Landes model presented a Pareto optimal outcome of plea bargaining; the Rhodes model introduced the notion that the courts are over-worked and under-staffed and, as a consequence, that plea bargaining is subject to many influences which are beyond the prosecutor's direct control. In developing a methodology for the treatment of offenders by the criminal prosecutor, Rhodes's model has been used as a starting point for the examination of case-specific factors which affect plea bargaining. Section 3.2 discussed the affect that the pre-trial delay and the prosecutor's budget have on plea bargaining outcomes, and Section 3.3 described the effect when the severity of the offense and the offender's criminal history are known. The analysis of the case-specific factors was restricted in that the prosecutor's budget and the pre-trial delay were assumed to not change and thereby confound the results. Other assumptions which facilitated the examination of the case-specific factors are the homogeneity of the offender population and the symmetry of the distributions of crime severity and the number of previous arrests. If any of these assumptions is violated, the case-specific analysis of the previous section is inappropriate since other factors which dictate the outcome when the pre-trial delay changes now affect the case-specific partial derivatives. Additionally, if the cost of

the case-specific information is passed along to the prosecutor, that analysis is invalid because the optimal mix of offenders will change as a result of the higher costs of fully prosecuting offenders.

In this chapter, Rhodes's model and two case-specific factors have both been examined under two different scenarios. The first scenario, Case I, assumes that a priori information is available to the prosecutor before he decides either to prosecute a defendant or to release him. For Case II, however, no a priori information is available. Intuitively, the assumption of Case I seems to more accurately describe the specific information analyzed here (viz, the prosecutor's budget, the pre-trial delay, and a defendant's crime severity and offense history). Thus, for the simulation model developed for this research, the plea bargaining component is based upon the assumptions of Case I, not Case II. Any information which the prosecutor is to receive is assumed to be available from the moment a case is assigned to the prosecutor.

## CHAPTER IV

### A NETWORK SIMULATION MODEL OF THE CJS

#### 4.0 Introduction

In Chapter II, the evaluation of the current state of the technology of CJS modeling showed how simulation models have demonstrated considerable promise for the holistic analysis required for the evaluation of sentencing and plea bargaining strategies. A model which combines the queueing, resource allocation, cost and recidivism components described in these earlier efforts would be an especially important contribution to the field. One such model, DOTSIM, apparently approached this goal, but it lacked detail in its recidivism component and a model of plea bargaining was nonexistent. Subsequently, in Chapter III economic models of plea bargaining were described in order to develop a foundation for creating a plea bargaining component in a simulation model of the Criminal Justice System. The mechanics of plea negotiations were discussed in length and the consequences of changes in the length of the pre-trial delay, in the size of the prosecutor's budget, and in the amount of case-specific information that is made available to the prosecutor were examined.

The purpose of this chapter is to describe a computer simulation model which possess the desired attributes.

#### 4.1 The Generalized Network Simulator

In order to incorporate the diverse dimensions of criminal justice simulation models into one effort, the Generalized Network Simulator (GNS)

has been selected as the simular vehicle for this thesis. Historically, GNS evolved from the General Evaluation and Review Technique Simulator (GERTS) series of network models [37] [69]. Combining into one simulator the queueing, resource allocation, and costing capabilities that were otherwise available in the Q, R, and C versions of GERTS III, GNS is a sophisticated tool for use by planners of a variety of systems including criminal justice. Although a description of GNS may be found in other references, an overview of its capabilities follows.

Unlike other network representations, GNS requires that the nodes represent activities and that the arcs portray precedence relationships between the nodes. GNS differs from many network flow models in that the nodes for these other models represent either the initiating or terminating events of the activity represented along the arc. In either case, entities travel through the network along the arcs. If multiple arcs leave a particular node, GNS allows the user to choose the method of arc selection: it may be probabilistic or it may be a special user-designed rule.

Technically speaking, the nodes of the GNS network are referred to as either nodes or boxes, the former representing an event with a duration of zero and the latter representing an activity with a positive duration. A certain type of box, called a queue box, also allows the model-builder to specify the maximum number of servers available which, when all servers are busy creates a queue of entities waiting to be served. Only one server is required to process each entity, but an unlimited number of resources of no more than 30 types may also be required to process each entity. An unlimited number of servers can be associated with each queue

box, but resources may be shared between two or more queue boxes.

GNS has several costing options which may be implemented at a user's discretion. First, there may be costs associated with the entire project (model): a one-time set-up cost and an overhead cost per time period. Second, there may be costs associated with each queue box: a one-time set-up cost and a cost of operating a box each time period. Finally, since each queue box may also require resources to process an entity, each resource may have a cost per unit time of use that is also attributed to the appropriate box. Hence, the costing capability is comprehensive.

The last of GNS's capabilities discussed here deals with the concept of the user-controlled box (or node). Such a box allows the user to create his own FORTRAN logic to augment the available facilities. In particular, GNS allows the start control box and the end control box. In the first case, the user provides additional logic to be executed whenever an entity leaves the associated queue and enters the in-progress list of the box. The end control box serves the same function as the start control box, however, the user's logic is executed only when an entity's service at the box is completed and it is ready to leave the facility. This capability to supply additional logic to the stochastic network is an asset for any simulation model; it has been used extensively for this model of the CJS.

Although GNS possesses many other features, those that have been mentioned are of primary use for the present analysis. (The interested reader is referred to [36], [37], [38], and [69] for further information.) The incorporation of these capabilities into a single model requires a

great deal of computer time and storage capacity. Since the computer in use is a CDC Cyber 74, the execution time of the model will have been reduced over the execution time of other hardware systems, but the core required to execute this model is still large compared to, say, JUSSIM II. However, since GNS already possesses the desired attributes for this model of the CJS, it is used with these precautions in mind.

## 4.2 The Simulation Model

### 4.2.1 Model Overview

The GNS model of the Criminal Justice System is displayed in Figure 1. It is a feedback model similar to that developed by Belkin, Blumstein and Glass, however, each offender is modeled separately in a manner similar to DOTSIM. By simulating each offender as he progresses through the CJS, the delays in the system can be simulated. In addition, the emphasis on the offender and the special capabilities of GNS enable the analysis of the effects that limited resources have on the system. Since the resources are frequently shared between two or more queue boxes, each offender must also compete for the resources that are available. Hence, the observed queueing behavior may be confounded by limited resources. This is one important contribution of this model to CJS analysis; the ability to model the effect of scarce resources in this manner has not been attempted heretofore.

The diagram in Figure 1 is drawn using the notation established for GNS [37] [69]. The boxes represent activities, while the circles and semi-circles represent events. Start and end control logic is represented by shading a portion of the box or node closest to the input or the output





of the activity. Queue boxes are represented as rectangles with a circle intersecting the box's inputs. Each queue box has associated with it exponentially distributed service times specified for each crime type. (Other service distributions could have been chosen, but were not for simplicity.) CJS resources are also specified; each server in the model corresponds to one unit of at least one type of resource. Thus, for each offender processed at a queue box, at least one resource unit is being consumed and its cost added to the cost of the system.

Whenever the portion of a node closest to its output is pointed, offenders are routed to one of the node's successor activities probabilistically. Unless specified otherwise, the branching probabilities for each arc are a function of the offender's crime alone. For boxes, if the corners on the output side of the box are removed, then branching probabilities determine where an offender will be routed. Unless otherwise directed, these probabilities are also functions exclusively of the offender's crime.

Another special event is the sink node. This node is differentiated from the other nodes by its half moon shape. The function of these nodes is to remove offenders from the simulation lists. For this particular model, this happens only if an offender dies (Node 3) or if he is never re-arrested (Nodes 7, 18, 27, 34, 35, 36 and 46).

Of the many attributes which could have been generated for each offender, only the following are actually saved for each offender:

1. Current Age
2. Race and Sex

3. Age at death
4. Career Criminal Cost
5. Total number of arrests
6. Types of offenses committed

The offender's age at death is stored to prevent the time consuming regeneration of this age. The extra storage capacity required to store this attribute is considered an acceptable trade-off to the extra simulation time needed to regenerate it whenever needed.

The crime categories simulated are the FBI's seven index offenses:

1. Homicide
2. Robbery
3. Aggrevated Assault
4. Burglary
5. Grand larceny
6. Auto Theft
7. Forcible Rape

These offenses have been chosen for the representativeness of their rates of commission vis-à-vis all other felonies and for the readily available data that exists. Each time an offender is arrested, it is assumed that he has committed only one offense. This assumption is consistent with earlier models; it simplifies the model considerably.

#### 4.2.2 The Cost Model

The individual offender orientation of this simulation model enables the calculation of the expected number of times an offender is arrested during his criminal career in addition to the expected career criminal cost. Both of these performance measures have been used in previous works

(cf., Chapter II). The manner in which an offender's career criminal cost is determined is very similar to that used by Pittman; all set-up costs are assumed zero. The fixed costs of operating the CJS per time period and of operating each queue box are also assumed zero. The only mechanism used to impute the cost of operating the CJS to each offender is through the usage of resources. The actual career criminal cost for the  $i^{\text{th}}$  offender,  $(\text{CCC})_i$ , is updated by the amount of each resource  $k$  required for processing him at activity  $e$  by the relation

$$(\text{CCC})_i = (\text{CCC})_i + \sum_k C_k T_{ei} R_{ek}, \quad (4-1)$$

where  $C_k$  is the cost of resource  $k$  per offender per time,  $T_{ei}$  is the processing time of offender  $i$  at activity  $e$ , and  $R_{ek}$  is one if resource  $k$  is required to process offenders at activity  $e$  and it is zero otherwise.

For this analysis it is assumed that ten different resource types are sufficient to describe the resource scarcity and queueing interaction. (See Table 4.) This level of aggregation, although not absolutely necessary, simplifies this model and it reduces the time required to collect the additional data that otherwise would be required. Since each resource unit at this level of aggregation most likely does not correspond to an actual server (e.g., judge or prosecutor), each resource must be distributed to the queue boxes which require the specific resource type, to an actual server (e.g., judge or prosecutor), each resource must be distributed to the various queue boxes whose  $R_{ek} = 1$ . Although the best way to distribute these resources is to conduct sensitivity studies on

the final model to determine how many units of each resource should be required by each modeled server to process a single offender, this has not been done. Instead, each queue box  $e$  which requires resource type  $k$  is assumed to use the resource as efficiently as any other processor. Hence,  $R_{ek} = 0$  or  $1$  for all  $e$  and  $k$ . The cost of each resource is therefore constant over all CJS processors. The actual cost of utilizing each resource and the maximum availability of each type is determined in the following chapter, Section 5.2.

Table 4. CJS Model Resources

Resource Number	Resource Type	Queue Box Numbers
1	Prosecution	23, 28, 37, 39
2	Police	5
3	Superior Court	37, 39
4	Other Courts	8, 9, 21, 25
5	Grand Jury	28
6	Juvenile Corrections	12, 13, 14, 15
7	Adult Incarceration	26, 40, 41, 51
8	Parole and Probation	42, 45
9	Pre-Trial Detention	10, 22
10	Indigent Defense	25, 39

What follows is a description of the model displayed in Figure 1 as well as of the assumptions and the mechanisms underlying this structure. Each remaining subdivision of the chapter examines one of the major components of the CJS: Police Subsystem, Prosecution and Court Subsystem, Correction Subsystem, Juvenile Justice Subsystem, and Recidivism Model.

#### 4.2.3 The Police Subsystem

Of all the subsystems in the model, the police subsystem is the least detailed as far as the actual CJS operation goes. The greatest number of artificial devices are employed here. This subsystem consists of four processors.

Table 5. Elements of the Police Subsystem

<u>Activity Number</u>	<u>Description</u>
1	Virgin Arrest Forecaster
2	Virgin Arrests
3	Offender's Death
5	Total Police Arrests

Box 1, Virgin Arrest Forecaster. This event generates at the beginning of each simulated month a forecast of the number of persons who are arrested for the first time for each of the seven index offenses. By assuming that the proportion of the total number of people arrested for crime  $j$  who have not been arrested previously is constant, the number of so-called virgin arrestees is determined for month  $t$  by

$$V_{jt} = N_j F_{jt} , \quad (4-2)$$

where  $F_{jt}$  is the forecast of the number persons arrested during month  $t$  for

crime  $j$  and  $N_j$  is the proportion of all arrested offenders who have not been arrested previously. The forecast  $V_{jt}$  is subsequently converted into  $V_{jt}$  first offenders by the logic of Box 1. Each simulated offender is entered into the lists which GNS uses to keep track of the entities which flow through the network, and each offender's attributes are created at that time. The attributes age at arrest, race and sex, and age at death are all generated immediately from empirical distributions. The remaining attributes, reserved for statistics collection, are also initialized at this time.

The graphical representation of Box 1 displayed in Figure 1 needs some explanation. The arc which feeds back onto this box represents the flow of a dummy entity. The box first generates this entity when the simulation begins. At the beginning of each month, this dummy entity completes service at Box 1 at which time it re-enters the box. Thus, this dummy entity serves as a timing mechanism. It is when the dummy entity re-enters Box 1 that the special logic of this box forecasts the number of first offenders who are arrested during the month and enters them into the lists of Box 2.

Box 2, Virgin Arrests. Although each offender is assumed to be arrested at either Box 4 (grand jury warrant) or at Box 5 (all other police arrests), the purpose of the intervening Box 2 is to delay the arrest of offenders so that all arrests do not occur at the beginning of each month. Instead, when Box 1 generates each first offender, it also generates a service time for the offender at Box 2 so that arrests for each crime category are uniformly distributed over the month.

Box 5, Total Police Arrests. The only queue box in the police subsystem, Box 5 allocates the cost of the police to each offender that is arrested without a grand jury warrant. The method selected to do this is perhaps overly simplified, but it is a satisfactory approximation. By assuming that the amount of police resources required to apprehend and charge an offender is the same regardless of whether or not he is a first-offender or a recidivist, the total police cost can easily be allocated. If it is further assumed that the processing time of this box is negative exponential with a mean of one day, the cost of using each police resource at Box 5 results in a probabilistic allocation of the total cost of police services. Because of the artificiality of the one day processing required at this box, the total processing times observed at the subsequent processors (i.e., initial hearing and juvenile intake) are necessarily reduced by one day.

Upon an offender's completion of service at Box 5, the end control logic then determines if an offender is to be routed to the juvenile intake hearing (Box 8) or to the initial hearing (Box 21). It is assumed that all juveniles enter the CJS at this box; rather than because of a grand jury warrant at Box 4.

#### 4.2.4 The Prosecution and Court Subsystem

Because the objective of this thesis is to evaluate alternative scenarios for plea bargaining, the prosecution and court subsystem is particularly detailed. This subsystem is composed primarily of the superior and criminal courts, the grand jury, and the initial arraignment hearings; thus, there exists sufficient detail for the implementation of the economic model of plea bargaining presented in the previous chapter.



The components of this subsystem are defined in Table 6.

Table 6. Elements of the Prosecution and Court Subsystem

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<u>Activity Number</u>	<u>Description</u>
4	Grand Jury Warrant
21	Initial Hearing
22	Adult Pre-Trial Detention
23	Prosecution
25	Lower (Criminal) Court
28	Grand Jury
29	"No Bill" from Grand Jury
30	"True Bill" from Grand Jury
31	Dead Docket or <u>Nolle Prosequi</u>
32	Arraignment Hearing
37	Superior Court Trial
39	Superior Court Guilty Plea or <u>Nolo Contendere</u>

---

The GNS events which correspond to the prosecutor's two decision points occur at Box 23, Node 30, and Box 32. This structure differs from that developed by Rhodes in that his prosecutor's first decision occurs both at Box 23 and at Node 30. This additional structure essentially allows the prosecutor to dismiss a defendant following the grand jury hearing (i.e., at Node 30) despite earlier evidence of the defendant's guilt. In addition, this model of the prosecutor's first decision further assumes that the prosecutor chooses those cases to be tried by the lower court. Therefore, the number of lower court hearings is also affected by the size of the prosecutor's budget, the superior court pre-trial delay, and such case-specific factors as the severity of an offender's crime and his previous arrest record.

The manner in which the offender flows are changed by these factors is essentially a heuristic one. For each of the arcs in this subsystem, the probability that an offender who committed crime  $j$  travels from activity  $b$  to activity  $d$  is defined as  $P_{bdj}$ . Each flow probability is then changed according to some function  $f_{bd}$  to yield a revised probability  $P'_{bdj}$  which includes adjustments for the factors mentioned in Sections 3.2 and 3.3,

$$P'_{bdj} = f_{bd}(P_{bdj}). \quad (4-3)$$

In addition, the nature of the function  $f_{bd}$  reflects both the decision point (activity  $b$ ) and the decision (that is, arc  $d$ ). This function is described at Box 23, Node 30 and Box 32.

Node 4, Grand Jury Warrant. The grand jury warrant is one of two ways by which an offender enters the Criminal Justice System; the other way is by police arrest (Box 5). This node represents the arrest of an offender because of the issuance of a warrant by the grand jury. Once an offender is apprehended, the presiding judge determines whether or not the offender should be detained (that is, jailed) while his case proceeds through the courts. If so, a dummy entity is created at Box 22, adult pre-trial detention, and it remains there until the corresponding offender is either released from the CJS or he is convicted and sent to corrections. Whether or not this dummy entity is created, the offender is sent to Box 28, the grand jury, immediately following the realization of Node 4.

Box 21, Initial Hearing. The initial hearing serves as a check

on the police. By requiring that evidence be presented to the presiding magistrate, it is the responsibility of the magistrate to determine if there is a reasonable suspicion that the offender actually committed the charged offense. If he determines the charges to be appropriate, the offender is sent to Box 23 for the prosecutor to investigate the case. However, if the evidence is deemed to be insufficient, the offender is released. For the purpose of this analysis, it is assumed that all arrested offenders proceed to Box 23; no one is released at this stage.

Since all offenders are assumed to proceed with further processing, the magistrate presiding at the initial hearing determines whether or not each offender should be jailed while awaiting trial. As at Node 4, a dummy entity is created at Box 22 if the offender is to be jailed.

Box 22, Adult Pre-Trial Detention. When the lower courts determine that an offender should be jailed while awaiting a trial, the offender becomes an additional financial burden on the CJS. To model this, Box 22 was created to access the cost of pre-trial detention to the offender's career criminal cost. The decision to detain an offender is made either at Node 4 following the issuance of a grand jury warrant or at Box 21 at the initial hearing. This decision is described probabilistically in this model, the probability of detention being a function of the crime category.

When an offender is to be detained, a dummy entity is created for immediate processing by Box 22. Removal of a dummy entity from detention is performed whenever the judicial proceedings of Boxes 25,

37 or 39 are completed by the offender or when the offender is released because the case has been dismissed (Node 54). Alternatively, it is assumed that an offender may also be released from detention immediately prior to his trial. At any of these locations, the total time spent in jail is determined for the dummy and the associated cost of servicing the entity is then added to the career criminal cost of the corresponding offender.

Box 23, Prosecution. This box represents the first decision point for the prosecutor in the plea bargaining process. As such, the special logic of this box must determine according to the description of Chapter III which offenders are to be released (Box 54), which cases are to be examined by the grand jury (Box 28), and which cases are to be tried by the lower court for having committed a misdemeanor (Box 25). According to the discussion in Sections 3.2 and 3.3, the decisions made at this point do not solely depend upon the merits of each individual case. Instead, the prosecutor is cast in a situation where limited resources restrict the outcomes of plea bargaining even though it is the prosecutor's objective to maximize the cumulative severity of the sentences handed down. Under this scenario, increasing the prosecutor's resources allows him to prosecute more offenders; thus, the probability that an offender is released to Box 54 is reduced while the probability of his being further prosecuted (that is, sent on to the grand jury hearing) increases. However, an increase in the delay that offenders experience while awaiting trials by the superior court reduces the number of defendants whose cases are prosecuted. In addition, it was

hypothesized that an above-average severity of a defendant's latest offense increases the prosecutor's inclination to continue with the case, and the number of previous offenses committed by an offender is also positively related to the flow probabilities which connect activities 23 and 28.

In implementing Box 23, each of the following state variables are taken into account at time  $t$  when determining the subsequent processing of each offender:

1. The current level of the prosecutor's resources,  $B_t$ ;
2. The current length of the superior court's (Boxes 37 and 39) pre-trial queues,  $Q_t$ ;
3. The current number of offenses committed by offender  $i$ ,  $C_i$ ;
4. The severity of the  $C_i$  offense committed by a defendant,  $S_i^*$ .

Since the analysis of Chapter III shows that any change in the offender flows depends upon the above four state variables, these variables in relation to their average values are used in this simulation model to implement the prosecutor's decision function  $f_{bd}$  at this activity as well as at the other two decision points at Node 30 and Box 32.

Specifically, the following relations affect  $f_{bd}$  in equation 4-3:

$$G_t = \begin{cases} \frac{B_t}{B_0} & \text{if the prosecutor's budget affects } P'_{bdj}, \\ 1 & \text{otherwise;} \end{cases} \quad (4-4)$$

$$H_t = \begin{cases} \frac{Q_t}{Q_0} & \text{if the pre-trial delay affects } P'_{bdj}, \\ 1 & \text{otherwise;} \end{cases} \quad (4-5)$$

$$I_i = \begin{cases} \frac{C_i}{C_0} & \text{if the offender's arrest record affects } P'_{bdj}, \\ 1 & \text{otherwise;} \end{cases} \quad (4-6)$$

$$J_i = \begin{cases} \frac{S_i^*}{S_0} & \text{if crime severity affects } P'_{bdj}, \\ 1 & \text{otherwise;} \end{cases} \quad (4-7)$$

where  $B_0$  and  $Q_0$  are the baseline values of the prosecutor's budget and the pre-trial queue, respectively, and  $C_0$  and  $S_0$  are defined as the expected values of the number of offenses per offender and of the severity of an offense. Although the function  $f_{bd}$  changes for each of the prosecutor's decision points, the function  $f_{23,d}$  is defined using the prosecutor's weighting function  $W_{ijt}$ , as follows:

$$P'_{23,d,j} = \begin{cases} \text{MIN.} \left( (W_{ijt} P_{23,28,j}), 1.0 \right), & \text{if } d = 28, \\ \left( 1 - P'_{23,28,j} \right) \left( \frac{P_{23,25,j}}{P_{23,25,j} + P_{23,54,j}} \right), & \text{if } d = 25, \\ 1 - \left( P'_{23,28,j} + P'_{23,25,j} \right), & \text{if } d = 54. \end{cases} \quad (4-8)$$

The prosecutor's weighting function is defined by the expression,

$$W_{ijt} = G_t I_i J_i / H_t. \quad (4-9)$$

This formulation of  $f_{23,d}$  ensures that

$$0 \leq P'_{23,d,j} \leq 1.0$$

for all  $d$  and  $j$ .

Box 25, The Lower (or Criminal) Court. The criminal court is a less expensive alternative for dealing with an adult offender than is the superior court. This court handles cases of a less severe nature than those appearing before superior court justices, thereby incurring a smaller cost per case because fewer court and prosecution resources are required. Referring to Rhodes's economic model in Section 3.2, the criminal court serves as a repository for those cases in which the convictability of the defendant is below the threshold requiring him to be sent to the superior court, but which is simultaneously above the minimum prosecutable value. Such cases are usually tried as misdemeanors.

After processing each case, the judge presiding over the criminal court either releases the defendant to Node 57 after dismissing the charges or he sentences the convicted offender to one of the forms of correction allowed misdemeanor offenders:

1. Jail for men (Box 26)
2. Jail for women (Box 51)
3. Probation (Box 42)
4. Fine (Node 43)
5. Suspended sentence (Node 44)

Each sentence is determined probabilistically based on the crime an offender committed and upon the fact that he was convicted by the lower

court. The latter factor serves to differentiate between felony convictions in the superior court and misdemeanor convictions in the lower court.

Box 28, The Grand Jury Hearing. The fundamental of the economic interpretations of plea bargaining is that the prosecutor is the only instrument of the courts which attempts to balance the immediate CJS-related costs of adjudication with the almost imminent social costs that will occur when an offender is released. The economists have modeled a prosecutor who maximizes the incapacitation term of all offenders, subject to the limitations of his budget. The cost to the prosecutor of handling a case depends upon the inherent convictability of the defendant, but as well upon the length of the pre-trial queue. The grand jury decision would also depend on the inherent convictability of a defendant; however, the assumption will be made that the grand jury is independent of the prosecutor and his budget, and, consequently, the state variables in equations 4-4 through 4-7. Thus, the grand jury simply examines the evidence against the defendant and determines the likelihood that he committed the offense. If the likelihood is below some pre-determined threshold value, then it releases the offender to Node 29; otherwise, the defendant is sent to Node 30 following the grand jury's decision to issue a "true bill."

Node 29, Grand Jury "No Bill". If the grand jury fails to indict an offender, a "no bill" condition is said to exist. Consequently, the defendant is released from the CJS to Node 54 and, the corresponding entity at pre-trial detention (Box 22) is purged from the model.

Node 30, Grand Jury "True Bill". When the grand jury indicts



an offender, a "true bill" is said to have been established and the offender is routed to this node for further processing. Following the issuance of a "true bill," the prosecutor must decide whether to arraign the defendant (Box 32) or to dismiss the case in spite of the indictment (Node 31, dead docket or nolle prosequi). Since the prosecutor is the decision maker at this stage, the same considerations are present as determined the offender's route following Box 23.

Referring to the definition of the prosecutor's decision function  $f_{23,d}$  in equation 4-8, since the decision at Node 30 is the same as at this earlier decision point, the weighting function is assumed to be the same as in equation 4-9. Since  $f_{bd}$  depends upon the decision point and the output arcs,  $f_{30,d}$  is defined as follows:

$$P'_{30,d,j} = \begin{cases} \text{MIN.} \left( W_{ijt} P_{30,32,j}, 1.0 \right), & \text{if } d = 32 \\ 1 - P'_{30,32,j}, & \text{if } d = 31. \end{cases} \quad (4-10)$$

Node 31, Dead Docket or Nolle Prosequi. Following a "true bill," the prosecutor still has the prerogative to dismiss a case by either declaring a dead docket or by nol-prossing the case. In either situation, the offender is routed from Node 30 to Node 31. Since Node 31 has a zero duration, an offender routed here is immediately released from the CJS to Node 54. If he was in jail awaiting adjudication, then the corresponding dummy entity at Box 22 is released simultaneously.

Box 32, Arraignment Hearing. If the prosecutor decides at Node 30 to pursue a case, an arraignment hearing is scheduled. At such a hearing, the defendant must plead to the indictment charges issued by

the grand jury. Depending on how he pleads, the defendant's case placed on the superior court's calendar either for a trial (Box 29) if he pleads not guilty or for a sentencing hearing (Box 37) if he pleads guilty.

Box 32 is the third and final decision point in this simulation model in which the prosecutor's decision is affected by the state variables defined earlier. If  $P'_{32,d,j}$  is defined similarly to  $P'_{23,d,j}$  and  $P'_{30,d,j}$ , then another weighting function must be defined to take into account the prosecutor's responses,

$$W'_{ijt} = G_t^H I_{ij} J_i. \quad (4-11)$$

The updated flow probabilities are defined by the following equation:

$$P'_{32,d,j} = \begin{cases} \text{MIN.} \left( W'_{ijt} P_{32,39,j}, 1.0 \right), & \text{if } d = 39 \\ 1 - P'_{32,39,j}, & \text{if } d = 37. \end{cases} \quad (4-12)$$

Following this arraignment, if an offender is in jail while awaiting trial, he may be released on his own recognizance. This decision is made probabilistically. If he is to be released, the dummy entity at Box 22 is purged from the model.

Box 37, Superior Court Sentencing Hearing. If the defendant pleads guilty or nolo contendere (no contest) to the charges filed against him at the arraignment proceedings (Box 32), his case is placed on the superior court's calendar; that is, his case is scheduled for a sentencing hearing. From the simulation's perspective, the

offender is entered into the service queue of Box 37. When the offender's case is finally presented to the court, a judge reviews the charges and the subsequent plea with the defendant, and he sentences him to an appropriate form of correction. Since the offenders sent to the superior court are usually felons, the correctional possibilities differ from those of the criminal court. For the superior court, the correctional states are:

1. Jail for men (Box 26)
2. Jail for women (Box 51)
3. Probation (Box 42)
4. Fine (Node 43)
5. Suspended Sentence (Node 44)
6. Prison for men (Box 40)
7. Prison for women (Box 41)
8. Parole (Box 45) following a term in prison (Boxes 40, 41).

An offender is sentenced to one of the above forms of correction by examining his conviction label (final charge). For convenience, this final charge is determined at either of boxes 37 or 39 rather than at Box 38 where it actually would be determined. (For simplicity, the final charge is not determined for the lower or the juvenile courts. Dispositions of cases at these hearings are based upon the crime category instead.) This artificiality is introduced to embed in the model the differences between the final conviction labels resulting from a trial conviction and those resulting from guilty pleas at Box 39. This device also facilitates the determination of the correctional state as a function of the final charge instead of the crime category.

According to Shin, [62] there exists a negative relationship between the amount of charge reduction and the severity of the ensuing sentence. Thus, this model is able to capture this aspect of plea bargaining although it shall not be investigated any further here.

Both the model which determines the final charge and the model which determines the correctional state are probabilistic. The former is based solely on the most recent arrest charge of an offender, while the latter is only based upon the final charge. The durations of the resulting sentences are also based upon the conviction label. (See Chapter V, Section 5.1.)

Box 39, Superior Court Trial. Whenever a defendant pleads not guilty to the arraignment charges, a trial is held by the superior court to determine his innocence or guilt. After proceeding through a series of legal maneuvers and delay tactics, the trial date is established and the case is placed on the court's calendar; however, in this model the processing time associated with Box 39 is assumed to include both the trial and the pre-trial maneuvers (called motions). Thus, the model assumes that the offender's case is first placed on the calendar (viz, placed in the pre-trial queue) and when it enters the processor, it is processed continually until a verdict and perhaps the sentence are delivered.

At the completion of the trial, the model determines probabilistically whether or not the defendant is guilty. The conviction probability is an empirical function of crime type. If the offender is not guilty, he is routed to Node 50, dismissal; however, if he is found

guilty a final conviction charge is determined probabilistically based on crime type. The corrections states to which the convicted offender may be sent are identical to those described for Box 37. The type and length of the sentence that each offender receives are also determined as at Box 37; however, the empirical values of the flow probabilities and the durations themselves may differ.

For offenders who are detained while awaiting trial the corresponding dummy entities are released from detention at Box 22 when the offender completes service at Box 39. This holds true for Box 37 as well.

#### 4.2.5 The Corrections Subsystem

For this simulation model, the Corrections Subsystem consists of all those boxes and nodes which represent potential dispositions of either the lower or the superior courts; juvenile corrections are considered a part of the Juvenile Justice Subsystem. The components which comprise the Corrections Subsystem are tabulated in Table 7.

Table 7. Elements of the Corrections Subsystem

<u>Activity Number</u>	<u>Description</u>
26	Jail for Men
40	Prison for Men
41	Prison for Women
42	Adult Probation
43	Fine
44	Suspended Sentence
45	Parole
50	Case Dismissal
51	Jail for Women

Whenever an offender is sentenced either to prison, to jail, or to probation, an exponentially distributed service time is generated whose parameter is a function of the conviction label, the manner in which the offender was convicted, and the offender's sex in the case of the jail and prison dispositions where separate facilities are maintained for each sex. The method of conviction affects the duration of each sentence in this model; the time spent at each correctional facility depends upon whether the offender

1. Was convicted by the lower court (Box 25),
2. Plead guilty to the superior court's prosecutor (Box 37),
- or
3. Was convicted by a superior court trial (Box 39).

For the offender convicted by the lower court, the final conviction label is assumed to be the crime category. Greater resolution for lower court convictions is unnecessary when the majority of cases are tried in the superior court.

Following his release from corrections, an offender is routed to either Node 56 or 57. These nodes determine whether or not the offender is re-arrested.

Boxes 26 and 51, Jail for Men and Women. Because a term in jail is a less severe punishment than a prison sentence whose duration far exceeds that of the jail disposition, the superior court (Boxes 37 and 39) is assumed to sentence offenders to prison, not to jail. Conversely, the criminal court does not sentence its offenders, who are usually convicted of misdemeanors or mild felonies, to the prisons; it

sentences convicts to jail. The reasoning behind this assumption is obvious. Since the prison is considered a harsh punishment that is reserved for society's worst, those offenders who are convicted of offenses by the lower court deserve a more lenient punishment for a less reprehensible crime. This simple distinction between the dispositions of each court is the only one of its kind formulated for corrections. All other dispositions are available to each court, even though case dismissal (Node 50) is not of course an alternative for the defendant who pleads guilty and is subsequently sentenced at Box 37.

Separating both the jail and the prison facilities along sexual lines guarantees to the analyst the flexibility to determine which offender category costs more in a career criminal cost sense. Because of the sexual and other offender-specific attributes, the modeled offender population can quite easily and realistically be decomposed according to the offender's traits when examining the efficacy of alternative policy scenarios. This important characteristic distinguishes this model from earlier modeling efforts, an example of such an evaluation is forthcoming in Chapter VI.

When an offender completes his jail sentence, he is released by the CJS to Node 57.

Boxes 40 and 41, Prison for Men and Women. As with the jails, the prison facilities are segregated according to the sex of the inmates; Box 40 represents the facility for men while Box 41 is the facility for women prisoners. As soon as an offender *i* arrives at either facility, the model generates the duration of the prison sen-

tence,  $T_i$ . However, since offenders frequently do not serve their entire sentence in prison, the model then generates the actual time spent in prison  $T'_{ic}$  by multiplying  $E_c$ , the proportion of the prison sentence actually served by an offender convicted of final charge  $c$ , by the original sentence duration,

$$T'_{ic} = E_c T_i. \quad (4-13)$$

After an offender spends  $T'_{ic}$  years in prison, he is automatically released on parole (Box 45). If he violates the conditions of his parole before his term is finished, it is assumed that he will be returned to prison to complete his original sentence. That is, the time an offender spends in prison after violating parole is:

$$T''_{ic} = T_i - T'_{ic}. \quad (4-14)$$

The probability of a parole violation is assumed to depend upon the offender's conviction label. The time that an offender is on parole is assumed to be exponentially distributed and independent of whether or not a parole violation is perpetrated.

Following an offender's completion of either a prison sentence or a term on parole, he is released from the CJS to Node 56 to determine if he recidivates.

Box 42, Adult Probation. One of the most frequently used forms of correction, the probationary disposition in this model is a normal implementation of a queue box. As with other processors in this subsystem, the sentence duration is a function of the final conviction label of the defendant. When an offender's sentence is completed, he



is also routed to Node 56.

Nodes 43 and 44, Fine and Suspended Sentence. The events represented by Nodes 43 and 44 represent milestones in the processing of the offender since any offender who is required to pay a fine or who is given a suspended sentence is not subsequently monitored by the Criminal Justice System for the current conviction. Thus, an offender is immediately released to Node 57 following his arrival at either Node 43 or 44.

Box 45, Parole. When the offender arrives at this box, he begins his time of parole. The average time served on parole and the probability of parole revocation are both assumed to be functions of the conviction offense; it is supposed that the conviction label is an accurate indication of the required parole term. In addition, it can be argued that the conviction label determines an offender's pre-disposition to abuse his right to a parole, thereby indicating the probability of revocation as well as the time between the beginning and the termination of the parole activity. Although casting the parole function in this manner does not allow the flexibility to specify separate time distributions for those offenders whose parole is revoked and for those who successfully complete their parole, it is believed that the resulting simplifications do not detract from the efficacy of the model when the parole activity is completed.

Depending upon the parole outcome, the offender is either released from the CJS to Node 56 or he is returned to prison (Boxes 40 or 41) to complete the original prison sentence.

Node 50, Case Dismissal. If following a trial by either the

lower court (Box 25) or the superior court (Box 39) the charges against a defendant are dropped, then the model directs the offender to Node 50. The purpose of this node is to distinguish between those offenders who are released from the courts and those who entered one of the correctional programs. After realizing this node, an offender is immediately released to Node 57.

#### 4.2.6 The Juvenile Justice Subsystem

The Juvenile Justice Subsystem (JJS) is a particularly critical component of the CJS because a substantial percentage of first-offenders are under age 18 (see Belkin, Blumstein and Glass). The processors which represent the JJS are shown in Table 8.

Table 8. Elements of the Juvenile Justice Subsystems

---

<u>Activity Number</u>	<u>Description</u>
8	Juvenile Intake Hearing
9	Juvenile Court Hearing
10	Juvenile Pre-trial Detention
12	Juvenile Incarceration
13	Juvenile Probation
14	Other Juvenile Correctional Institutions
15	Juvenile Informal Adjustment

---

Box 8, Juvenile Intake Hearing. Following his arrest by the police (Box 5), the intake hearing is a youth's first introduction to the judicial process. The purpose of this hearing is similar to that of the initial hearing of the adult courts. It determines

whether or not the youth's arrest was justified and how he is to be further processed by the CJS. Although the processing of offenders at the intake hearing varies widely between criminal justice systems, it is usually an informal, closed-to-the public hearing whose outcomes are typically one of the following:

1. The juvenile is released (Node 52) because of his obvious innocence in having committed the specified offenses;
2. The youth is sent to the juvenile court (Box 9) because the nature of the crime warrants special consideration by a magistrate in a formal court proceeding;
3. The offender is sent to the superior court (via Box 23) since his crime is sufficiently heinous to warrant the harsher sentences issued by the adult courts.

Another outcome of this hearing is also frequently observed. It occurs when an offender pleads guilty to the charges against him. For this model, however, it is assumed that only the preceding three outcomes occur and that the juvenile court always determines the youth's innocence or guilt. Furthermore, the intake hearing is assumed to be independent of the plea bargaining issues with which the prosecutor in the superior court must wrestle.

When the intake hearing begins, the presiding judge determines whether or not the offender should be detained by the Juvenile Justice System while his case proceeds. If he is detained, a dummy entity is created at Box 10, the juvenile pre-trial detention. If following the intake hearing, the juvenile is released from the JJS to Node 52, then the corresponding dummy entity in the list of Box 10 is destroyed.

If the offender is sent to Box 23 for processing as an adult, however, the dummy entity at Box 10 is released and the model determines whether or not the juvenile will be detained before receiving the disposition of the superior court. In this case, the probability that the juvenile is jailed prior to his trial is assumed to be identical to the probability for an adult who is arrested for the same offense.

Box 9, Juvenile Court Hearing. The juvenile court hearing is a formal hearing wherein a youth's innocence or guilt is ascertained and an appropriate sentence issued. Following this hearing, if the defendant has been detained by the Juvenile Justice Subsystem he will be released from detention (i.e., the corresponding dummy entity residing at Box 10 is released) prior to any subsequent processing. Additionally, if a juvenile is to be tried in the regular courts, he is again subject to pre-trial detention, however, this time in the jail used for detaining adult offenders.

The dispositions of the juvenile court are more numerous than for the intake hearing. In addition to those which are identical to the dispositions of the intake hearing, the following correctional programs for juveniles are considered:

- a. Incarceration (Box 12)
- b. Probation (Box 13)
- c. Other Institutions (Box 14)
- d. Informal Adjustment (Box 15).

Box 10, Juvenile Pre-Trial Detention. Pre-trial detention for

juveniles at Box 10 is treated in an identical manner as that for adults at Box 22. When a youth first enters the Juvenile Justice System, the model determines if he is detained while awaiting further processing. If so, a dummy entity is created by the model and begins processing at this box. The entity is subsequently released whenever the offender reaches a point in his processing that he is no longer to be detained. Thus, the dummy entity is released either when the offender is transferred to Box 23 for processing as an adult, when he is released to Node 52 following the court or intake hearings, or when he is sentenced to the care of a juvenile correctional program.

Boxes 12, 13, 14 and 15, Juvenile Corrections. For this model, juvenile corrections has been aggregated under the following processors:

1. Incarceration (Box 12)
2. Probation (Box 13)
3. Other Institutions (Box 14)
4. Informal Adjustment (Box 15).

Although it undoubtedly plays a role in the actual JJS, the parole of offenders is not explicitly considered in this model.

Whenever an offender is sentenced to one of these programs, the model determines the actual time spent under the auspices of the JJS as a function of the crime category. Thus, the juvenile subsystem does not possess the detail of the adult court dispositions since the latter includes the final charge of the defendant. As was stated earlier, plea bargaining is not considered to be an important factor in the juvenile courts.

When the juvenile is released from any of these four correctional programs, he is routed to Node 53 which determines if he is re-arrested.

#### 4.2.7 The Recidivism Model

The apparatus which models offender recidivism consists of those nodes and boxes which have not been described elsewhere. The one exception to this is sink Node 3. This special event collects statistics on offenders who die. For lack of a better location, Node 3 is assumed to be part of the recidivism apparatus shown in Table 9.

Table 9. Elements of the Recidivism Model

---

<u>Activity Number</u>	<u>Description</u>
3	Offender Death
7	Juvenile Desistence
18	Juvenile Desistence, Correctional Release
19	Juvenile Recidivism Delay
20	Juvenile Re-arrest
27	Criminal Desistence, Prosecution Release
34	Criminal Desistence, Jail Release
35	Criminal Desistence, Miscellaneous Corrections Release
36	Criminal Desistence, Probation Release
46	Criminal Desistence, Prison or Parole Release
47	Adult Recidivism Delay, Correctional Release
48	Adult Recidivism Delay, Non-Correctional Release
49	Adult Re-arrest
52	Juvenile Court Release
53	Juvenile Corrections Release
54	Release by Prosecution
56	Release from Severe Corrections
57	Release From Lenient Corrections

---

There are not, it is also assumed, any resources associated with recidivism. To do so would embed the social cost of crime in the present model, but this will not be attempted for the present.

Nodes 52, 53, 54, 56 and 57, Release by the CJS. Whenever an offender is released by the CJS, the model determines at one of these nodes whether or not he is re-arrested at any time in the future. The model makes this decision about each offender by examining his sex and current age. If a particular offender does not recidivate, he is routed to the appropriate sink node which represents the offender's desistence in criminal activity. Otherwise, if the offender does recidivate, he is sent to either Box 19, 47 or 48, which delays his arrest for another crime.

Nodes 7, 18, 27, 34, 35, 36 and 46, Criminal Desistence. These nodes represent the outcome that an offender does not recidivate in the sense that he is never again arrested. The purpose of these nodes is to purge a "rehabilitated" offender from the model and to collect statistics on such offenders. The following statistics are collected whenever an offender enters any sink node in the model (including Node 3):

1. Age and sex of offender
2. Number and type of offenses committed
3. Point of release from CJS (viz, sink node number)
4. Career criminal cost.

In addition, the time series of the average number of offenses committed per offender and of the average career criminal cost are collected on offenders who desist during each six month period of the simulation.

These performance measures are discussed further in the following chapters.

Boxes 19, 47 and 48, Recidivism Delay. The purpose of these three boxes is to postpone the re-arrest of an offender who has been released from the CJS and who it has been determined recidivates. As was discussed in Chapter II, the delay time between an offender's release from the Criminal Justice System and his re-arrest has been shown by Stollmack and Harris [64] to be distributed negative exponentially. based upon this finding, the distribution of these delay times is assumed in this model to be a negative exponential whose single parameter,  $\lambda$ , is dependent upon both the age of the offender at the time of his release from the CJS and upon either the stage at which the offender was released or the type of correctional program he was subjected to. Thus, this component possesses a greater degree of resolution than its predecessors JUSSIM II or, certainly, DOTSIM. (See Section 2.2.)

The major difference between these three boxes is that recidivists who were released from Node 56 are routed to Box 47 whereas the recidivists who are released from Nodes 54 and 57 are routed to Box 48, and those released from Nodes 52 and 53 are routed to Box 19. The reason for this differentiation is to be able to monitor the time series of adult recidivists who are severely penalized for their offenses (Box 47), or who are either only lightly penalized or who are not penalized at all (Box 48), and the time series of juvenile recidivists (Box 19).

Boxes 20 and 49, Juvenile and Adult Recidivist Arrests. Whenever an offender recidivates, either Box 19, 47 or 48 determines the timing



of his re-arrest and either Box 20 or Box 49 predicts the offense for which he is arrested. As discussed in Section 2.2, a model which has been used successfully to predict a recidivist's new crime is a first order Markov chain. In using this model, like the previous efforts, an offender's next crime is solely a function of his last offense. Thus, it is assumed that an offender's demographic variables do not affect these transition probabilities.

Once the new offense has been determined, the offender is routed to either Node 4, the event which signifies the issuance of a warrant by the grand jury, or more frequently to Box 5, all other police arrests. If the offender is under the legal age of an adult, then it is assumed that he is always arrested at Box 5 as opposed to having been served a warrant at Node 4.

Node 3, Offender's Death. Before completing this description of the GNS model of the Criminal Justice System, this important node must be discussed. When processing an offender  $i$  in this model, if the duration  $T_e$  of any activity  $e$  causes his age to exceed his death age  $A'_i$ , the duration of the activity is redefined to be the difference between the offender's current age  $A_{ti}$  and his death age. Namely,

$$T'_e = \begin{cases} T_e, & \text{if } A'_{ti} - A_{ti} \leq T_e \\ A'_{ti} - A_{ti}, & \text{if } A'_{ti} - A_{ti} > T_e. \end{cases} \quad (4-15)$$

If  $T'_e = A'_{ti} - A_{ti}$ , the offender is routed to Node 3 following the completion of service at activity  $e$ , and statistics on the age, sex, career criminal cost, and number of criminal arrests of the offender are tabu-

lated; the offender is then permanently removed from the system.

#### 4.3 Summary

This concludes the description of a simulation model of the Criminal Justice System. In the following chapter, this model is implemented using empirical data and it is subjected to validation testing. In Chapter VI, experiments with alternative plea bargaining policy scenarios are conducted to demonstrate how this model may be used to determine the effect of changes in the current plea bargaining strategies on global CJS performance measures. The precise nature of these tests will be explained further at that times.

## CHAPTER V

## MODELING A SPECIFIC CRIMINAL JUSTICE SYSTEM

5.0 Introduction

The subject of this chapter is the implementation of the model developed in the previous chapter. The sample data is principally from the CJS of Sacramento County, California, although certain statistics have been taken either from other systems or from the nation's averages. Regardless of the source, care has been taken to ensure the normative behavior of this model so that the results of the tests conducted in the following chapter may be of interest to CJS practitioners in general.

In implementing this model of the Criminal Justice System, the following items must be discussed. First, the data itself must be described. Where it comes from; when was it collected; what assumptions does its use force upon the model; and what transformations, if any, were required before it could be used? These issues are addressed in Section 5.1. Then, since the model of the CJS requires that several parameters and that the levels of the criminal justice resource expenditures be initialized prior to the model's use, the initialization of this model is described in Section 5.2. Finally with the model having been operationalized, the issues surrounding model validation are discussed. Both aggregate and component behaviors are examined in relation to the actual CJS being modeled as well as for the model's internal consistency. Model validation

is the topic of Section 5.3.

Upon closing the discussions of model validity, this model of the CJS is fully implemented and ready for experimentation.

### 5.1 Sample Data

This section describes the data used in implementing the model of the CJS. Although the input variables and their values are described in the appendices, the purpose of this section is to describe the data sources, any manipulations required to transform the data into its final form, and the assumptions which accompany the usage of particular data. Much of the data focuses on the CJS of Sacramento County; however, frequent references are made to national statistics collected by the Department of Justice. National statistics have only been resorted to whenever local statistics have not been readily available.

The organization of this section follows closely the organization of the CJS itself in that each subsystem's inputs are discussed separately. (See also Appendices A and B.)

#### 5.1.1 Police Data

The empirical data required for the police subsystem deals with the first-offender forecasts, the characteristics of these first offenders, and the branching ratios of Box 2.

First-Offender Forecasts. As stated in Chapter IV, the number of first offenders who are arrested during any month  $t$  for crime  $j$  can be described by equation 4-2 as,

$$V_{jt} = N_j F_{jt} ,$$

where  $N_j$  is the constant proportion of all arrestees who have never before been arrested and  $F_{jt}$  is the total number of arrests made at time  $j$ . Deutsch's [24] empirical linear stochastic forecasting models are used for the forecasting function of the total number of arrests for crime  $j$ ; however, since his models forecast the number of occurrences of each crime instead of the number of arrests, additional assumptions are necessary. Let Deutsch's forecast at time  $t$  for crime  $j$  be  $D_{jt}$ . If a constant clearance rate  $C_j$  can be assumed for each crime and if the average number of offenders  $O_j$  who are arrested for a cleared offense is also constant for each crime, the expression

$$F_{jt} = O_j C_j D_{jt}$$

holds and  $(C_j D_{jt})$  is the forecast of the number of crimes cleared.

The forecasting functions developed by Deutsch are seasonal integrated autoregressive, moving average models. The preference for using such dynamic models should be obvious: they enable the testing of experimental hypotheses under the premise that the aggregate crime rate is growing and seasonal. Thus, even though such models are not available for Sacramento County, because Deutsch does provide parameter estimates for Los Angeles County, and because of the proximity of these two counties, the Los Angeles County forecasts will be scaled down to represent Sacramento County crime rates. The first-offender arrest rate for Sacramento County, then, is

$$V_{jt} = N_j O_j C_j D_{jt} / M_j \quad (5-1)$$

where  $M_j$  is the ratio of the Los Angeles County crime rate to the Sacramento County crime rate for each crime  $j$  and  $D_{jt}$  is Deutsch's forecast for Los Angeles County. Equation 5-1 can be re-written for simplicity as

$$V_{jt} = \Delta_j D_{jt} / M_j \quad (5-2)$$

where

$$\Delta_j = N_j O_j C_j$$

is constant for each crime  $j$ .

Deutsch [24] gives the parameter estimates for the models used to compute  $D_{jt}$ . Because of the form of these models, thirteen months of initial values and thirteen months of observed errors between the forecast and the observed crime rate are required to initialize these models. The Los Angeles data from January, 1974 to January, 1975 are used for this purpose. The  $N_j$  are computed using 1969, 1970 and 1971 California Offender Based Tracking Statistics (OBTS) [16]. After separating the Sacramento County offenders from the remainder of the population, the number of the offenders arrested for each index crime who had no previous arrest records or who had arrest histories but no criminal convictions were compiled. The percentage of the total number of Sacramento County offenders charged for crime  $j$  who met either of the above criteria is  $N_j$ . Although this approximation is merely that, more reliable estimates could not be found in the time allowed and these at least yield a relativistic statement of the true fractions.

The crime clearance rates,  $C_j$ , are taken from the 1974 Uniform Crime Reports (UCR) published by the FBI [29; p.43]. The average number of persons arrested for each cleared offense,  $O_j$ , is assumed to be one for each crime type. The reason for this assumption (even though, intuitively, it seems that  $O_j > 1$  for all  $j$ ) is that the UCR statistics, the primary source of arrest data, themselves have several limitations (see Sellin and Wolfgang, [60]). One of these limitations is that only the most severe offense is reported for any arrestee. Although it seems that  $O_j$  should be greater than unity, the decline in the actual number of persons arrested per clearance brought about by those offenders whose arrest actually clears several crimes results in an indeterminate  $O_j$ . Thus,  $O_j$  is set to one for simplicity.

A value for the forecast divisor  $M_j$  is established, for reasons to be disclosed later, in Section 5.2.

First Offender Attributes. In describing offenders in this model, several attributes for each first offender must be generated upon his creation in the model. Although many demographic variables could have been used to differentiate between categories of offenders, only the offender's sex is used to distinguish between the classes. (While the age of an offender is also an attribute of each offender, this variable is not used to distinguish between subpopulations.) The differentiation of the offender population along ethnic, racial or other designation is also possible for the model as presently designed, but creating additional classifications was not attempted

in order to reduce the data necessary for this example. The following statistics are required for each offender category and for each crime  $j$ :

1. The percentage of the first offender population who belong to offender category  $k$  and who are arrested for crime  $j$ ;
2. The average age of offenders whose attributes are  $(j,k)$ ,
3. The minimum and maximum ages of all  $(j,k)$  offenders;
4. The standard deviation of the ages of the  $(j,k)$  offenders.

These statistics were assembled from the California OBTS data base on offenders from Sacramento County for the seven index offenses. The actual values are shown in Appendix B. As the distribution of offender ages demonstrates gamma qualities, the corresponding means and standard deviations are converted within GMS to the parameters of this distribution. Thus, when an offender is arrested, his age is determined probabilistically using the parameters of the gamma distribution adapted from the empirical values in items 2, 3 above.

The average remaining lifetime of an offender whose current age is  $a'$  is used to determine the age at which an offender dies. This statistic is readily available from any almanac [66, p. 963]. Here, the remaining lifetime is assumed to be the mean of a negative exponential distribution; thus, because the exponential distribution is memoryless, the number of persons who die during any interval  $\Delta t$  would be uniformly distributed for each group of offenders whose age is  $a'$ . An offender's age at death is determined stochastically immediately upon his first arrest.



Branching Ratios, Box 2. The arcs emitting from Box 2 and directed toward Node 4 and Box 5 are defined by branching probabilities for each of the index crimes. These statistics are taken directly from the 1974 UCR [29; p. 175].

#### 5.1.2 Prosecution and Court Data

Because this subsystem is the most complex in the model, the data requirements for this component exceed those of the others. The following items are required:

1. Service distributions for the processors
2. Branching probabilities for the network arcs
3. Pre-trial detention probabilities
4. Final charge transition matrices for superior court convictions and guilty pleas
5. Court disposition probabilities for superior and criminal courts
6. Crime severity measures for plea bargaining

Service Distributions, Boxes 21, 23, 25, 28, 37 and 39. The service distributions used for the queue boxes which are a part of this subsystem have all been determined empirically based upon data from the California OBTS [16]. One bit of information available from this data base is the prosecutor's disposition:

1. Felony
2. Misdemeanor
3. No prosecution

It is assumed that a felony disposition means the defendant's case is to be tried in the superior court and that a misdemeanor is to

be tried in the lower court. The OBTS average delay between the time that an offender is charged and his subsequent disposition by the courts (viz, dismissal, acquittal, conviction) can be used to determine the processing times for this subsystem's processors.

The statistics available from OBTS are assumed to be based upon offenders who are arrested (Box 5) and who proceed with an initial hearing (Box 21) and prosecution (Box 23). As shall be seen shortly, this assumption facilitates the extraction of service times for the remaining court processors as well. For the initial hearing, the OBTS data base has no capability for giving this average processing time so the delay time shall be assumed to average one day regardless of the crime committed. This assumption is generally consistent with laws requiring a maximum delay for this hearing to be completed.

Now, consider the disposition where the prosecutor dismisses a defendant's case. Using the diagram of the CJS model in Figure 1, if it can be assumed that the prosecutor dismisses a case only at Box 23, the OBTS average delay between an offender's charge and his final dismissal is precisely the processing time of Box 23. This data, it turns out, is available from Sacramento County, and the average times are listed in Appendix B.

For the felony disposition, the defendant is routed from the prosecutor (Box 23) to the grand jury (Box 28). Assuming he is also arraigned (Box 32), either a trial may take place (Box 39) or he may plead guilty (Box 37). For the purpose of associating a processing time with each of these boxes, the average time between the determina-

Table 10. Average Court and Prosecution Processing Times

j CRIME	(A) $T_{21,j}$	(B) $T_{23,j}$	(C) $T_{28,j}$	(D) $T_j$ felony	(D)-(B)-(C) $T_{39,j}$	(E) $T_{37,j}$	(F) $T_j$ misdem.	(F)-(B) $T_{25,j}$
1. Homicide	1.0	8.5	7.0	45.9	30.4	.6	35.3	26.8
2. Robbery	1.0	6.8	7.0	31.5	17.7	.6	13.9	7.1
3. Assault	1.0	10.8	7.0	28.9	11.1	.6	18.1	7.3
4. Burglary	1.0	8.7	7.0	25.4	9.7	.6	15.0	6.3
5. Larceny	1.0	12.6	7.0	28.7	9.1	.6	17.3	4.7
6. Auto Theft	1.0	6.0	7.0	22.9	9.9	.6	17.2	11.2
7. Rape	1.0	10.0	7.0	30.5	13.5	.6	19.0	9.0

Note: Columns (A), (C) and (E) are assumed values.

Columns (B), (D) and (F) are from the California OBTS data base; 1969, 1970, 1971. [16]

tion of the charge and the sentence is tabulated. By assuming the average processing time needed by the grand jury for any case is seven days, the average time required by the superior court can be determined by subtraction:

$$T_{39,j} = T_j^{\text{felony}} - T_{23,j} - T_{28,j}$$

where  $T_{b,j}$  is the average processing time at box  $b$  for an offender arrested for crime  $j$ , and  $T_j^{\text{felony}}$  is the average time between the charge and the sentencing of an offender who has committed a felony according to the prosecutor's disposition of the case. These values for Sacramento County are summarized in Table 10. The processing time needed by the superior court when an offender pleads guilty is assumed to be uniformly distributed between 0.2 and 1.0 days since specific data is not readily available.

Finally, for the sample of offenders whose disposition by the prosecutor sends them to the lower court, the average processing time can be computed by the expression

$$T_{25,j} = T_j^{\text{misdemeanor}} - T_{23,j},$$

where  $T_j^{\text{misdemeanor}}$  is the average time between an initial hearing and the lower court's disposition. These values are also tabulated in Table 10.

By assuming that each processing time follows a negative exponential distribution, the average service time for each processor given by crime category completely describes the service distribution. The distribution of service times for processor  $b$ , crime  $j$  is

Table 11. Computation of Branching Ratios for Box 23

j CRIME	(A) TOTAL DEFENDENTS*	(B) FELONY DISPOSITION*	(C) MISDEMEANOR DISPOSITION*	(D) NO PROSECUTION*	$\frac{(B)}{(A)}$	$\frac{(C)}{(A)}$	$\frac{(D)}{(A)}$
1. Homicide	170	106	19	45	.624	.112	.265
2. Robbery	687	417	29	241	.607	.042	.351
3. Assault	1204	414	301	489	.344	.250	.406
4. Burglary	1839	948	314	577	.515	.171	.314
5. Larceny	582	232	138	212	.399	.237	.364
6. Auto Theft	698	303	66	329	.434	.095	.471
7. Rape	216	103	24	89	.477	.111	.412

\* Source: California OBTS data base; 1969, 1970, 1971 [16].

$$f(t) = \frac{1}{T_{b,j}} \exp \left( -t/T_{b,j} \right).$$

Branching Ratios, Boxes 23, 28, 32 and Node 30. Because of the assumptions made in determining the service distributions of the superior court trial (Box 39), all offenders are routed to the arraignment proceedings (Box 32) following a grand jury hearing (Box 28). That is, a "true bill" (Node 30) is issued by the grand jury and the prosecutor waives his option to declare a dead docket (Node 31) for every case. The assumptions are necessary, as will be recalled, because of the nature of the data available from OBTS. Since only three prosecutor dispositions are described in the OBTS data base, the above assumptions have enabled the calculation of the average processing times of the queue boxes in the subsystem.

The OBTS data base also yields the branching probabilities at the prosecutor's station (Box 23). These values are computed directly by determining the fraction of offenders handed each disposition (felony, misdemeanor, acquittal) for each of the index crimes. Those fractions, then, are the branching probabilities of the corresponding arc on the network diagram. These ratios are computed in Table 11.

Unfortunately, the OBTS data set does not contain the type of plea submitted by a defendant at the arraignment proceedings. Hence, to determine the branching ratios at Box 32, another source of information is required. Although data on the U.S. District Courts is not exactly what is needed here, the annual reports from the Department of Justice [2] do make statistics available which

Table 12. Computation of Branching Ratios for Box 32

	(A) Total Defendants	(B) Total Defendants	(C) Guilty Pleas	(D) Court Trials	$\frac{(D)}{(A)-(B)}$	$1 - \frac{(D)}{(A)-(B)}$
1. Homicide	138	36	62	40	.608	.392
2. Robbery	2365	337	1473	555	.726	.274
3. Assault	736	179	388	169	.697	.303
4. Burglary	285	44	212	29	.880	.120
5. Larceny	4824	706	3438	680	.835	.165
6. Auto Theft	1861	277	1308	276	.826	.174
7. Rape	79	19	42	18	.700	.300

\* Includes Nollo Contendere cases.

could be considered to be rough estimates of the true data. The actual statistics collected are the probabilities of an offender's going to trial or of his pleading guilty to the charges, given that he does one or the other. Since this is what is needed for the branching probabilities of the arcs emitting from Box 32, these estimates are used. The computations are shown in Table 12 for the fiscal year 1975.

Pre-Trial Detention Probabilities. The pre-trial detention model requires that an adult be detained just prior to the initial hearing (Box 21) if he is to be detained at all. This decision is resolved stochastically: the probability that an offender is jailed at any time before trial is a function of the offense committed. For these values, the 1974 Sourcebook of Criminal Justice Statistics [74; p. 87] has been consulted. Although the desired information is still not directly available from this reference, a survey is reported from which a surrogate measure has been computed. The survey reported that, of the 88 participating pre-trial release projects,  $P_{20,j}$  percent used their jail as an alternative to releasing a defendant on his own recognizance when the crime is  $j$ . Although these ratios are not necessarily even close to the branching probabilities expected for any one CJS, the national average should be close to these values reported by this survey. Thus, taking the potential for misrepresentation into account, these values are assumed.

However, it should be noted that equally imprecise estimates



have been obtained for the probability that an offender who is detained before trial is still detained following the arraignment hearing (Box 32). For these estimates, an implementation of the JUSSIM model was consulted [20; p. 126]. For this study of offender flows in Allegheny County, Pennsylvania, 2507 offenders (30.3% of all offenders present at the initial hearing) were in jail while the courts processed their cases, whereas only 1078 (13.0% of all offenders present at the initial hearing) were still in jail while awaiting the disposition of the court. By assuming that those in jail while awaiting trial were also in jail during the initial hearing, the ratio  $P'_{20,j} = \frac{1078}{2507} = .430$  for all crimes  $j$ , can be interpreted as the probability that an offender who is jailed during the initial hearing is still in jail during the trial.

Charge Transition Matrices. In designing the plea bargaining model, originally it was decided to separate the processes which determine an offender's conviction offense from those which determine the sentence duration. Thus, if a defendant were to plead guilty, the logic of Box 37 would determine both his conviction offense and his sentence, but it would do so independently. As the model evolved, this capability was designed into both processors of the superior court (Boxes 37 and 39). However, acquiring realistic data for each processor has proven to be a difficult task. The following assumptions have been made:

1. The probability that an offender who committed crime  $j$  is convicted by a court trial for charge  $c$ ,  $p_{jc}$  is identical to the probability  $p'_{jc}$  of an offender pleading

guilty to charge  $c$ ;

2. Only nine conviction charges are possible:
  - a. First degree murder
  - b. Second degree murder
  - c. Manslaughter
  - d. Robbery
  - e. Aggravated Assault
  - f. Burglary
  - g. Grand larceny
  - h. Auto theft
  - i. Forcible rape
3. The probability of disposition  $d$  occurring given charge  $c$  is not necessarily the same for the defendant who pleads guilty and for the defendant who is convicted at a trial;
4. The expected durations of particular dispositions  $S$  are not necessarily the same.

These assumptions allow the simulation of differential sentencing policies for offenders who are convicted by trial and for those who plead guilty.

With the assumption that  $p_{jc} = p'_{jc}$  for all  $j$  and  $c$ , the task of data collection is simplified. The charge transition matrix for convictions,  $H = \{p_{jc}\}$ , is equal to the charge transition matrix for guilty pleas,  $H' = \{p'_{jc}\}$ . To determine  $H$ , the OBTS data for Sacramento County is used to compute the probability that an offender who is both arrested for crime  $j$  and who is subsequently convicted for crime  $j$ .

Table 13. Computation of Charge Transition Matrix

CHARGE CRIME	(A) Homicide	# (B) Murder 1, given Homicide	# (C) Murder 2, given Homicide	# (D) Manslaughter given homicide	(A) (B) Murder 1	(A) (C) Murder 2	(A) (D) Manslaughter	*	*	*	*	*	*
HOMICIDE	.845	.473	.108	.419	.400	.091	.354	.028	.127	0	0	0	0
ROBBERY	0	.473	.108	.419	0	0	0	.782	.029	.003	.162	.003	.019
ASSAULT	.006	.473	.108	.419	.003	0	.003	.017	.948	.011	.011	.006	0
BURGLARY	0	.473	.108	.419	0	0	0	.010	.020	.857	.098	.012	.002
LARCENY	0	.473	.108	.419	0	0	0	0	.010	.029	.914	.048	0
AUTO THEFT	0	.473	.108	.419	0	0	0	.007	0	.014	.055	.925	0
RAPE	0	.473	.108	.419	0	0	0	.020	.143	.041	0	0	.796

\* Values determined from Sacramento County OBTS data base.

# Values determined from U.S. District Court data.

Then, U.S. District Court data [2; p. 423] is used to compute the conditional probability of the first and second degree murder, and manslaughter conviction labels given that a homicide has occurred. Since the OBTS data gives  $P(\text{homicide})$ ,

$$P(\text{murder 1}) = P(\text{homicide}) P(\text{murder 1} \mid \text{homicide})$$

$$P(\text{murder 2}) = P(\text{homicide}) P(\text{murder 2} \mid \text{homicide})$$

$$P(\text{manslaughter}) = P(\text{homicide}) P(\text{manslaughter} \mid \text{homicide}).$$

These computations and the  $p_{jc}$  are shown in Table 13.

Superior Court Disposition Probabilities. One of the major reasons for selecting the U.S. District Court data for the computation of the charge transition matrix is that these courts also distribute data on the dispositions of defendants for the charges selected above [2; p. 423]. The disposition probabilities for defendants who plead guilty are computed directly from this data. For the disposition of a defendant convicted by a trial, the following relation is assumed to hold for the conviction states (i.e., for imprisonment, probation, fine, suspended sentence):

$$P(\text{disposition } d) = P(\text{conviction for charge } c) \times \\ P(\text{disposition } d \mid \text{conviction} \\ \text{for charge } c).$$

The probabilities on the right hand side of the above expression are computed from the U.S. District Court data. The probability of an acquittal at a trial also comes directly from this data set. These estimates are included in Appendix B. Note that these probabilities

are entertained without regard to the offender's sex.

Lower Court Disposition Probabilities. Another reason for using the U.S. District Court data in determining the superior court disposition probabilities is that the OBTS data available for Sacramento County seems to be biased toward those defendants who are convicted. Thus, a more representative array of felony dispositions are possible by using the comprehensive federal court data. For the lower court (Box 25), however, this precision is not as critical since the focus of this model of the CJS is plea bargaining in the superior court. The OBTS data from Sacramento County is, therefore, an adequate source for dispositions based on crime type but not conviction label. Usage of the OBTS data does require certain assumptions:

1. The decision to jail an offender is made independently of his sex;
2. The jail disposition (Boxes 26, 51) in the model includes the OBTS jail, jail and fine, and jail and probation sentences;
3. The suspended sentence disposition (Node 44) is composed of the unsuperived probation and the other dispositions described in the OBTS data.

These results from the OBTS Sacramento County data base are also shown in the appendix.

Crime Severity. The relative severity of each crime category is required for one set of hypotheses concerning the model of plea bargaining. The average severity of each index offense has been determined by Heller and McEwen [33; p. 246] based upon the Sellin-

Wolfgang seriousness scale [60]. The estimates needed are borrowed from their analysis and are displayed in Appendix B.

### 5.1.3 Corrections Data

For the corrections subsystem, there are two general data requirements. The first is the sentence durations for the prisons, jails, probation and parole, and these must be distinguished by type of conviction:

1. Superior court guilty plea (Box 37)
2. Superior court trial conviction (Box 39)
3. Criminal court conviction (Box 25)

Since the parole term is determined independently of the other dispositions, the entire issue of parole data is treated separately in this section.

Lower Court Sentence Durations. Because prison is not an option for sentencing the defendant at a lower court hearing, only jail and probationary sentence lengths are required for the disposition of such cases. The expected durations of these sentences have been computed from the Sacramento County OBTS data base under the same set of assumptions needed to determine the disposition probabilities. The results are shown in Appendix B.

Superior Court Sentence Durations. Jail, it will be remembered, is not a disposition open to the superior court defendant. Therefore, only the prison and probation sentence lengths are required here. For the probationary sentences it shall be assumed that the method of conviction (i.e., guilty plea versus trial) does not impact the length of the sentence. Because of the high cost of the

prison disposition, however, the expected duration of a prison term is assumed to depend on the method of conviction.

Since the OBTS data does not distinguish between the plea bargained and the trial convictions, the U.S. District Court statistics [2; p. 423] shall be used in conjunction with certain results of Shin [62] to determine the expected prison sentence based upon the method of conviction and the conviction label. Shin is one of the few empirical sources which has compared the observed sentencing disparities between plea bargained and court trial convictions. His study is based on robbery and assault offenses; it showed that the average prison sentence for 23 defendants who were convicted at a trial was  $L_{n.g.} = 6.0$  years while for 411 similar defendants who pleaded guilty the average sentence was  $L_g = 3.2$  years. The weighted average of these prison sentences,

$$\bar{L} = \frac{23(6.0) + 411(3.2)}{23 + 411} = 3.35 \text{ years,}$$

can be used to compute the relative severities of the guilty plea sentence,  $S_g$ , and of the trial sentence,  $S_{n.g.}$ :

$$S_g = \frac{L_g}{\bar{L}} = 0.95$$

$$S_{n.g.} = \frac{L_{n.g.}}{\bar{L}} = 1.79.$$

By assuming that  $S_g$  and  $S_{n.g.}$  are constant for all nine convictions labels  $c$ , approximate prison sentences for each label can be computed by taking the average prison sentences found in the

literature,  $\mu_c$  and multiplying them by  $S_{g.}$  and  $S_{n.g.}$  to determine the expected sentencing disparities. Since the prison sentence data available from the U.S. District Courts [2; p. 423] is grouped by the length of the sentence, the expected duration for each charge  $c$  is

$$\mu_c = \frac{\sum_g f_c(g)x(g)}{\sum_g f_c(g)},$$

where  $f_c(g)$  is the frequency for the  $g^{\text{th}}$  group of sentences for charge  $c$  and  $x(g)$  is the average sentence for the  $g^{\text{th}}$  group. Because of the method of reporting this data, the following is assumed:

$g$	<u>Sentence Duration Limits</u>	<u>Assumed Average Duration</u>
1	duration $\leq$ 1 year	$x(1) = .5$ years
2	1 year < duration < 3 years	$x(2) = 2$ years
3	3 years $\leq$ duration < 5 years	$x(3) = 4$ years
4	duration $\geq$ 5 years	$x(4) = 20$ years

Both the expected prison sentences and the prison sentences for guilty plea and trial convictions are computed in Table 14.

Table 14. Computation of Prison Sentences for Guilty Plea and Trial Convictions

$c$	CHARGE	$\mu_c$	$\mu_{c \ S_g}$	$\mu_{c \ S_{ng}}$
1.	Murder 1	18.80 years	17.86 years	31.77 years
2.	Murder 2	13.14	12.48	23.52
3.	Manslaughter	6.12	5.81	10.96
4.	Robbery	8.60	8.17	15.39
5.	Assault	3.94	3.74	7.05
6.	Burglary	5.72	5.43	10.24
7.	Larceny	4.27	4.05	7.64
8.	Auto Theft	4.52	4.29	8.09
9.	Rape	10.56	10.03	18.90



Because of the assumption that the probationary sentence does not change between the guilty plea defendant and the defendant convicted by a court trial (given the same conviction label), the OBTS data base can be used to determine the expected length of such a sentence because it does not distinguish between methods of conviction. The results from an analysis of the Sacramento County defendants yields the expected durations found in Appendix B. Note that the sentence length is assumed to be the same for the three conviction labels of homicide.

Parole Data. Moseley and Gerould [47; p. 54] have shown that significant differences exist between a man and woman's ability to obtain parole. For the conviction labels  $c$  used in this model of the CJS, their results demonstrate that the average time that a man actually spends in prison,  $a_c$  is longer than for the woman,  $a'_c$ . However, by dividing by the average prison sentence,  $\mu_c$ , the proportion of the sentence actually served before parole can be determined as a function of the sex of the offender. (See Table 15.)

Table 15. Computation of the Proportion of the Prison Sentence Actually Served Before Parole

$c$	CHARGE	$a_c$	$a'_c$	$\frac{a_c}{\mu_c}$	$\frac{a'_c}{\mu_c}$
1.	Murder 1	6.75	3.67	.359	.195
2.	Murder 2	6.75	3.67	.514	.279
3.	Manslaughter	2.33	1.67	.381	.273
4.	Robbery	3.18	1.93	.369	.224
5.	Assault	1.75	1.33	.444	.233
6.	Burglary	1.83	1.25	.320	.219
7.	Larceny	1.33	1.17	.312	.274
8.	Auto Theft	1.50	0.83	.332	.184
9.	Rape	7.00	2.08	.663	.197

Once an offender is paroled (Box 45), he may violate the conditions of his release, causing his parole to be revoked and his return to prison. Once again, Moseley and Gerould [47; p.55] give some insight into such violations. They state that 22% of their sample violated parole within two years. For this example, then, it will be assumed that the time between the initiation and the revocation of an offender's parole is exponentially distributed and stationary across all charges; furthermore, 22% of the entire paroled population will be returned to prison after an average time of two years on parole.

#### 5.1.4 Juvenile Justice Data

The Juvenile Justice Subsystem has only three data requirements: the branching probabilities of the intake hearing (Box 8) and of the juvenile court (Box 9), the service distributions of these two processors and of the juvenile corrections processors (Boxes 12, 13, 14, 15), and the pre-trial detention probabilities.

Service Distributions for Boxes 8, 9, 12, 13, 14 and 15. It has been extremely difficult to get data on the processing of juvenile defendants, but one major reason for this is the variety of ways in which juveniles are treated by the CJS since only recently does there seem to be any real consistency in juvenile offender processing [21]. Because of this data deficiency, the processing times for the intake hearing and the juvenile court hearing are taken from a study of delinquency cases in Denver [21]. According to Cohen, the author of

this study, "...it took an average of 76 days from the time a case reached the intake division of the court until a decision..."

[21; p. 13] is made as to the court's disposition. Although the processing times of specific crimes are not discussed, if it is assumed for this model that each hearing requires 38 days, then the total average processing time for both of these processors is equal to that described, 76 days.

Another reason that it has been difficult to acquire data on juvenile processing is the secrecy surrounding both the handling of juvenile cases and the correction of juvenile offenders. This last reason is why no empirical data has been found to estimate the service distributions of the various juvenile correctional programs and why several assumptions are necessary to activate this section of the model. It is assumed that the processing times for juvenile incarceration (Box 12) are equivalent to the probation sentences for the adult offenders reported in OBTS. Although these juvenile sentences are not as severe as those for prison, they do reflect the need to incapacitate the juvenile. (See Appendix B.)

Whenever a juvenile is informally supervised (Box 15), the average processing time is assumed to be equivalent to the average jail sentence an adult would receive in the criminal court (Box 25). This data, then, is also obtained from the OBTS data base for each crime category.

The sentencing of a juvenile to a youth farm or similar institution is realized in this model when he is sentenced to Box 14. Here, the average processing time is set to the average of the

$(\sigma_0^2 - \sigma_N^2)/\sigma_N^2$  large provides that  $r_k^0$  will resemble a white noise process. Consequently, it is not useful for identifying  $N_t$  or  $\mu_t^j$ . When the aberration is an innovation, then  $r_k^0$  will reflect the behavior of the AR(p) polynomial in the noise model. Fitting the indicated AR(p) noise model and checking for lack of fit in its residuals should isolate the aberrant innovation and allow for it to be estimated along with the noise model.

When  $|\delta|$  is moderate,  $r_k^0$  again cannot be relied upon to identify either  $N_t$  or  $\mu_t$ . When the aberration is an observation, it masks  $r_k$  in  $r_k^0$ , and it is expected that lower order AR and MA noise model polynomials will be identified. However, for an aberrant innovation, the correct order of the AR(p) noise model should be identified, while the order of the MA(q) component may be underestimated. In either case, examination of the model's residuals may correct these identification errors, but there is no guarantee that this will always be the remedy.

### 3.3.3 Identification of Multiple Aberrations

In fact, the difficulties in identifying a time series model when only a single aberration exists are minor when compared to the case when multiple aberrations may be found in the data history. Table 6 summarizes the effects on  $r_k^0$  of multiple aberrant observations or innovations. Once again, three regions of the signal-to-noise ratio are identified.

As for the solitary aberration models, when  $\sigma_0^2 \doteq \sigma_N^2$ ,  $r_k^0 \doteq r_k$  can be used to identify the noise model. Since  $\delta(\tau_i) \doteq 0$  for each  $\tau_i$  period at which an aberration occurs, it may be difficult

ratios for Box 8 can be computed by assuming that the branching probabilities for juveniles tried as adults is identically zero for all crime types. The assumed correspondence between the Denver dispositions and the model's dispositions are shown along with the computed branching probabilities in Table 16.

Table 16. Computation of Branching Ratios for Boxes 8 and 9 for Crimes of Violence and for Crimes Against Property

Denver Disposition	Model Box	Violent Offenses	Property Offenses	P(disposition, given violent offense)	P(disposition, given property offense)
1	52	216	901	.397	.521
2	12	41	47	.125	.057
3	13	128	357	.390	.431
4	14	131	230	.399	.277
5	15	28	195	.085	.235

Pre-Trial Detention for Juveniles. As data does not appear to be available on the subject of pre-trial detention for juveniles, the probability that a juvenile is so detained is assumed equal to the comparable adult value. This assumption holds over all seven index crime categories.

#### 5.1.5 Recidivism Data

Four data types are required for the recidivism model used in conjunction with this model of the CJS:

1. The crime switch matrix
2. The recidivism probabilities
3. The recidivism delay times
4. The mortality rates

Although the last item is not related to recidivism per se, it should be remembered that it has been included as part of this apparatus for lack of more appropriate location.

The Crime Switch Matrix. This matrix is used at Nodes 20 and 49 to determine the crime for which an offender is arrested following his release from the CJS. It is composed of probabilities which have been assumed invariant to such factors as the offender's age, type of release and sex. Since Blumstein and Larson [12] have already developed and successfully used such a matrix, theirs is also used here.

The Recidivism Probabilities. The probability of recidivism was assumed in Chapter IV to be a function of an offender's age and sex. The major reason for this assumption is the conclusions of Robison and Smith [58] who site the apparent ineffectuality of alternate correctional programs in deterring recidivism. In fact, these two authors go so far as to state that little difference exists between the correctional programs they studied in reducing the rate of recidivism. Given their conclusions, it makes sense that recidivism would be more predictable given the characteristics of the offender. Estimates of the recidivism probabilities are given for a three year follow-up study in the FBI's 1974 Uniform Crime Reports [29; p. 50]. Although these probabilities may be understated because of the relative shortness of the follow-up period, they are used without adjustment here. These values are reported in Appendix B.

The Recidivism Delays. Although the recidivism probabilities are functions of the offender's personal characteristics (age and sex), it seems reasonable that the delay between an offender's release from the CJS and his subsequent re-arrest be a function of the type of CJS disposition for his last offense. Although there does not exist any empirical evidence to either support or refute this premise, it is assumed for this implementation of the CJS model. To determine recidivism delays, Stollmack and Harris [64] show that the delay distribution for recidivism can appropriately be described by a negative exponential distribution. These results are used here.

The 1974 Uniform Crime Reports [29; p. 51] give probabilities of recidivism based upon the two desired factors. Since these statistics were collected as part of the three year follow-up study mentioned earlier, if the process is assumed stationary, the average time until re-arrest,  $t$ , can be determined by solving

$$P(t \leq 3 \text{ years}) = \int_0^3 f(t) dt$$

where  $f(t)$  is the density function of the delay process. But since Stollmack and Harris have shown that

$$f(t) = \beta^{-1} \exp(-t/\beta) \quad ,$$

the average time between release and re-arrest,  $\beta^{-1}$ , can be determined as follows:

$$P_3 = P(t \leq 3 \text{ years}) = \int_0^3 \beta^{-1} \exp(-t/\beta) dt$$

$$P_3 = P(t \leq 3 \text{ years}) = 1 - \exp(-3/\beta)$$

and

$$\beta = \frac{-3}{\ln(1 - P_3)} \quad (5-3)$$

Thus, by computing a value of  $\beta$  for each index offense and each disposition using  $P_3$  from the UCR statistics, the desired delay distributions are completely defined. The computed average times are shown in Appendix B.

The Mortality Rates. Offender mortality rates are required in the event that a modeled offender does not desist in committing offenses. The mortality rates used for this model assume that an offender's longevity is not affected by his criminal status. The average remaining lifetime for a person of a particular age group is given in most almanacs [66; p. 963]. The values used for this model are shown in Table 17.

Table 17. Average Remaining Lifetime of Offenders Who Are  $a$  Years Old

Age Grouping	Average Remaining Lifetime, Males	Average Remaining Lifetime, Females
$10 < a < 15$	57.8	65.6
$15 < a < 20$	53.0	60.7
$20 < a < 25$	48.3	55.8
$25 < a < 30$	43.9	51.1
$30 < a < 35$	39.6	46.4
$35 < a < 40$	35.2	41.7
$40 < a < 45$	31.0	37.2
$45 < a < 50$	26.8	32.7
$50 < a < 55$	23.0	28.5
$55 < a < 60$	19.4	24.5
$60 < a < 65$	16.3	20.7
$65 < a < 70$	13.5	17.2
$70 < a < 75$	10.9	13.8



## 5.2 Model Initialization

The next phase required for implementation of this model of a criminal justice system is its initialization. This phase entails the fixing of several parameters which depend upon the realization of the queues in the network. Specifically, it will be recalled that a divisor which relates the crime rate of Los Angeles to that of Sacramento County is needed for the virgin arrest forecaster. This divisor is determined first. Next, since the queues themselves must be allowed to build up to a condition of steady-state, the length of the period during which the transient response is no longer evident is determined. The final requirement for initializing the model is to determine an appropriate cost for each resource and upper bounds on their usage. The cost of each resource is determined based upon actual costs and the level of usage in the model.

### 5.2.1 The Forecast Divisor

For the input to this model, forecasting functions developed by Deutsch [24] have been borrowed. Earlier in this chapter, it was decided that a divisor  $M_j$  for each crime  $j$ , was needed to scale the forecasts of Deutsch's Los Angeles crime rates in order to approximate the rates for Sacramento County. Recall that the virgin arrest forecast at time  $t$ , defined in equation 5-2, is

$$V_{jt} = \Delta_j D_{jt} / M_j ,$$

where  $D_{jt}$  is Deutsch's forecast at time  $t$  of crimes reported, and  $\Delta_j$  is a constant relating  $D_{jt}$  to the virgin arrest rate for crime  $j$ .

To determine  $M_j$ , the 1974 Uniform Crime Reports [29] were examined and the appropriate ratios developed. These  $M_j$  are shown in Table 18 along with the resulting initial values of the corresponding crime rates,  $V_{j1}$ .

Table 18. Determination of the Forecast Divisor,  $M_j$

crime	$M_j$	$V_{j1}$	$M'_j$	$V'_{j1}$	$M''_j$	$V''_{j1}$
Murder	37	1	20	1	30	1
Robbery	25	2	20	3	30	2
Assault	22	8	20	9	30	6
Burglary	10	21	20	11	30	7
Larceny	5	66	20	17	30	11
Auto Theft	16	5	20	4	30	3
Rape	15	2	20	1	30	1

In trying to simulate the model, it was discovered that the proposed initial forecasts caused the model to terminate prematurely. That is, the build-up of offenders in the queues exceeded the capacity of the model prior to the estimated run length. (At this point, the run length was approximated at 50 years, 25 years each for initialization and experimental periods. This would at least allow a criminal career of average length to be simulated during each epoch.) The executable form of this model requires 221,600 octal words on a CDC Cyber 74, segmenting the program as much as practical. Because of its already large size, increasing the capacity of the GNS list processing arrays was considered undesirable. Thus, the decision was made to make  $M_j$  a constant over all crime categories in order to scale the forecasts

to a manageable size. After trying several values, notably  $M'_j = 20$ , the run length of 50 years was still not achieved; however, when  $M''_j = 30$ , a little extra capacity would be available for increasing the experimental period of the simulation.

Table 18 summarizes these steps. It should be noted that, although the magnitude of the differences  $(V_{jl} - V_{kl})$  has changed for any pair of crimes  $j$  and  $k$ , when  $M_j$  is set to either 20 or 30, ranking the  $V'_{jl}$  or the  $V''_{jl}$  on the basis of magnitude maintains the same order on  $j$  as when the  $V_{jl}$  are ranked. Thus, setting  $M_j = 30$  preserves the relative level of exposure of crimes in this modeled CJS as expected in the actual Sacramento County CJS.

Another observation worth noting is that the overall behavior of the various queues in the model did not change between  $M_j = 20$  and  $M_j = 30$ . It appears, therefore, that the modeled CJS is sensitive only to the magnitude of  $M_j$  and that differences in  $M_j$  result only in proportional changes in the model's behavior. This should be true so long as the resource levels are unconstrained. In a constrained environment, however, a reduction in  $M_j$  accompanied by a proportional reduction in the resource constraint, might result in significant differences in the two responses.

#### 5.2.2 The Initialization Period

Prior to actually experimenting with a simulation model which deals with queueing phenomena, two parameters must be determined. One parameter, the initialization run length, prescribes the amount of time that the model is simulated in order to pre-load the queues in the

network. The second parameter is normally called, simply, the run length. It is the amount of time simulated beyond the initialization period in which the experiments are performed. Thus, any simulation experiment may be considered to be composed of initialization data (which is usually discarded, according to Kleijnen [41; pp. 69-73]) and of experimental data.

To determine the length of the initialization period, a sample run of the model is executed and an attempt is made to ascertain when the transient phase of the network is completed. The boxes which collect the recidivists who are released from the CJS are the critical processors of the network. When these processors reach steady-state, the remainder also should be in this condition since the other processors eventually route their offenders to one of the recidivism boxes:

1. Juvenile Recidivism (Box 19)
2. Adult Recidivism, Harsh Disposition (Box 47)
3. Adult Recidivism, Lenient Disposition (Box 48)

Examining the simulated time series of the number of offenders stored at each box (Figure 2), an immediate observation is that none of these plots stabilizes at an average level. However, with the growth in the crime rates and the recycling of offenders back into the CJS, the level of activity at each processor is expected to grow at some near constant rate. Thus, rather than looking for the stabilization of a plot, the stability of a process is sought. From Figure 2, the three plots all seem to have entered a period of constant growth beyond the 20<sup>th</sup> year. The length of the initialization period is, therefore, 20 years. This

value also has a great deal of intuitive appeal as the average criminal career should last approximately 7 years [29; p. 48], thereby allowing most of the offenders who were arrested at day one of the initialization period to desist in their criminal pursuits by the time  $t = 20$  arrives.

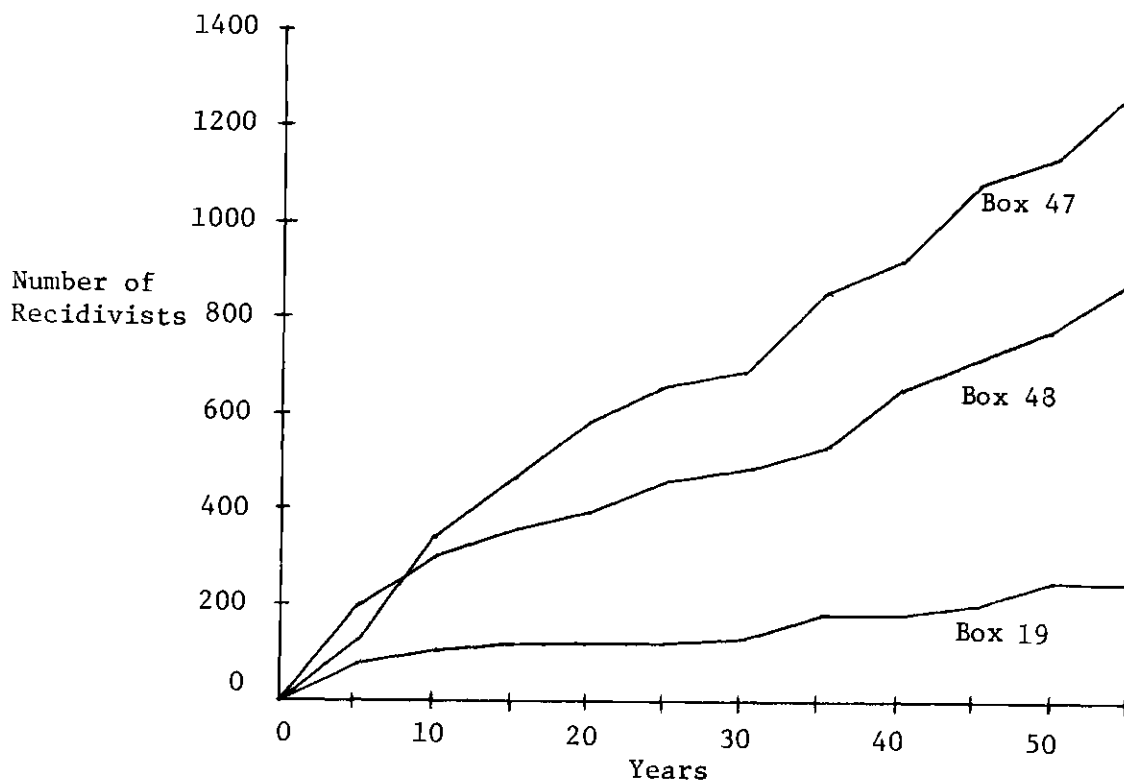


Figure 2. Time Series of Recidivists Released From the CJS

To determine the run length of the experimental epoch, most discrete event simulations compute the number of observations required to test a hypothesis at a desired level of significance. Such a procedure is used in order to minimize the cost of executing the simulation model; however, it is usually done only for models which are stationary in both the mean and in the variance of the performance measure of interest. Since this model of the CJS is not to be used for the testing of specific hypotheses, other factors must be considered:

1. The length of the average criminal career
2. The capacity restrictions of GNS
3. The responsiveness of the model to parameter changes.

Considering the first two factors together, the approximate length of the normative criminal career is 7 years and the capacity of GNS allows on the order of 50 years of simulated history including the initialization phase. Therefore, the length of the experimental period should be at least 7 years but not much bigger than 30. Taking the model's responsiveness into account, the initialization period required 20 years to stabilize. Because of this slowness to reach steady-state and the need to test changes to the model, the longest possible run length should ensure that the model will achieve steady-state following a perturbation. Further analysis of GNS's capacity reveals that a total of 55 years can safely be simulated. Therefore, the run length is taken to be 35 years.

### 5.2.3 Resource Costs

The final two steps required to initialize this model of the CJS is to determine the resource constraints and costs. Because of the level of resource aggregation proposed in Chapter IV, there does not exist a one-to-one correspondence between a unit of resource  $k$  and a particular resource of the actual CJS. That is, the resources of this model are imaginary, contrived using certain notions of how resources are normally used. This method of implementing resources should be enhanced before definite conclusions are drawn from this model, but for the current work such an artifice simplifies the data collection requirements and at the same time it should not detract from the experimental results.

To determine the cost of each resource in the model, a sample run has been made and the average number of offenders  $\Lambda_k$  using each resource  $k$  determined for the first 12 months of the experimental phase of the simulation. (See Table 19.) The total annual cost of each resource,  $A_k$ , is based upon U.S. government statistics for Sacramento County [71; pp. 171, 197, 228, 247, 273]. These estimates are divided by the number of days in each simulated year to arrive at the average daily cost of each resource,  $A'_k$ . The expected cost per resource unit per offender day is simply the ratio of  $A'_k$  to  $\Lambda_k$ . This ratio,

$$C_k = A'_k / \Lambda_k.$$

Table 19. Computation of the Expected Daily Cost Per Offender

k	$\Lambda_k$	$A_k$	$A'_k = A_k/360$	$C_k = A'_k/\Lambda_k$
Resource Number	Average Usage	Total Annual Cost(x 1000)	Average Daily Cost(x 1000)	Expected Daily Cost Per Offender
1	21.75	\$ 3330	\$ 9.25	\$ 425
2	6.42	9270	25.75	4010
3	2.75	1534	4.26	1550
4	15.00	1813	5.04	336
5	7.17	1223	3.40	474
6	63.17	2348	6.52	103
7	413.58	3008	8.36	20
8	960.00	3469	9.64	10
9	8.33	436	1.21	145
10	4.50	882	2.45	544

is used as the cost of processing an offender for one day using resource k. Both the total operating cost of the entire CJS and the contribution of resource k to an offender's career criminal cost are based upon the value of  $C_k$  (cf., Chapter IV).

#### 5.2.4 Resource Constraints

In developing the resource constraints for this example, it seems that not all of the resources should possess a fixed upper bound on their consumption. The reason is that the model does not currently take into account several interdependencies which naturally arise under certain conditions. For example, if a policy is tested which causes



a surge of offenders to enter the prisons, then an upper bound would cause a queue of offenders waiting for prison. Since such a queue does not normally develop in the prison system, other mechanisms must be at work. Either,

1. Offenders who have nearly completed their sentences are released;
2. The prosecutor foresees that the prisons are becoming overcrowded and he begins offering greater charge reductions for guilty pleas, thereby reducing the number of defendants who are eligible for prison sentences;
3. Extra capacity is acquired.

Although these alternatives are by no means indicative of the responses that would be taken in all circumstances, they do show the types of adjustments that can be made with increased demands on a CJS processor. Since the objective of the runs in the following chapter is to examine scenarios which deal specifically with the prosecutor and the superior court, only the resources which deal directly with these two entities should be constrained. Therefore, the response of the CJS to increased demand on processors with unconstrained resources is assumed to be the third option in the above prison example. Furthermore, the acquisition of new capacity is assumed to cost nothing; only the cost of processing offenders by CJS resources is ever considered in this example.

Only two resource types are to be constrained, the prosecutor and the superior court resources (numbers 1 and 3, respectively). A test run of the unconstrained model shows that the usage of both in-

creases at a slow but apparently exponential rate. The following model is postulated:

$$B_{t,k} = B_{t-1,k}(1 + q)$$

$$\text{or} \quad B_{t,k} = B_{1,k}(1 + q)^{t-1}, \quad (5-4)$$

where  $B_{t,k}$  is the resource constraint for resource  $k$  at month  $t$ , and  $q$  is the rate of growth. For an annual growth rate  $r$  compounded monthly,

$$q = r/12. \quad (5-5)$$

Figure 3 shows the usage of the prosecutor's resource for the unconstrained run along with three proposed constraints for  $r = 2.0\%$ ,  $2.5\%$  and  $3.0\%$  growth. (The initial value  $B_{1,k}$  is determined by inspection, based upon estimates of  $\Lambda_k$ ,  $\sigma_k$ , the sample variance of resource usage. When additional test runs were made for each of the values of  $r$ , the  $r = 2.0\%$  run caused the number of offenders in the model to exceed GNS's capacity. Likewise, the  $r = 3.0\%$  run was unsatisfactory because little queueing resulted. The  $r = 2.5\%$  run is satisfactory, however, and this rate of growth is used throughout the remainder of this research. A similar analysis performed for the superior court resource selected a rate of growth of  $2.5\%$  as well.

For some of the work using this model, an alternative formulation of the budget constraint 5-4 shall be required. The particular constraint that is required might be referred to as the subsidy version of 5-4, where at time  $t_0$  the upper bound on resource  $k$  experiences a percentage increase in the level of resources available. To develop this constraint mathematically, define the unit impulse function as

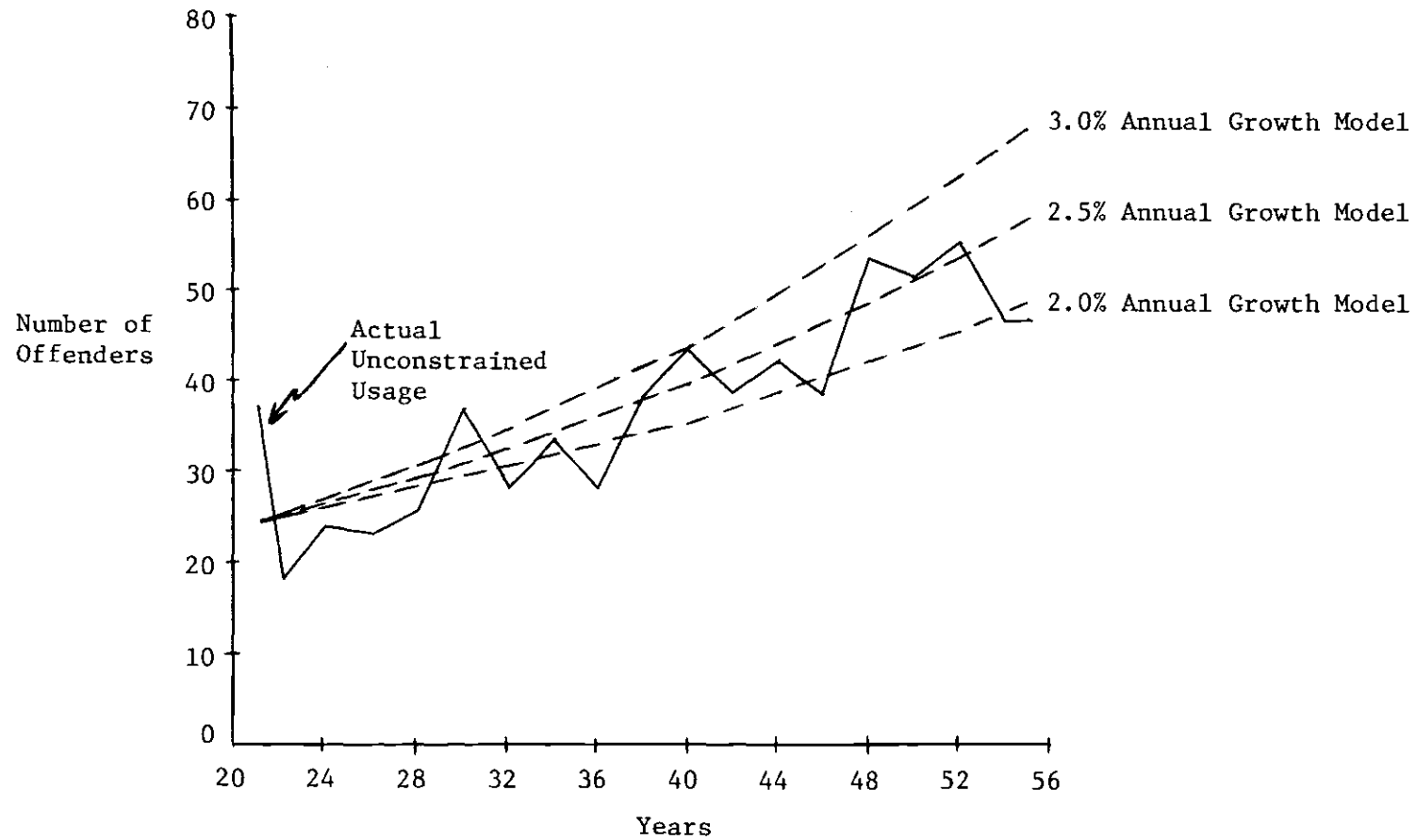


Figure 3. Comparison of Unconstrained Usage of the Prosecutor's Resources to Three Candidate Growth Models

$$\delta_{t_0}(t) = \begin{cases} 1 & \text{if } t = t_0, \\ 0 & \text{otherwise.} \end{cases}$$

If  $s$  is defined as the subsidy rate, then equation 5-4 can be re-written for the subsidized resource constraint, as,

$$B_{t,k} = (1 + s\delta_{t_0}(t))(1 + q)^{t-1}B_{1,k}. \quad (5-6)$$

For the purpose of this research, the time  $t_0$  at which the subsidization of resource  $k$  would begin immediately follows the initialization epoch.

### 5.3 Model Validation

Evaluating model validity or, from the empiricists perspective, model adequacy, is a difficult task that should require considerable effort on the part of the analyst. Shannon [61] has identified the various viewpoints which model builders have espoused over the years. There is the rationalist perspective which supports a model on the ground that the basic assumptions of the model are intuitively appealing. The empiricist, on the other hand, requires support for the model's validity in the form of statistical or other tests of the assumptions and resulting outputs. Several such tests are, of course, available in the literature [41] [30][61]. The pragmaticist, meanwhile, concentrates on the input-output transformation of the model, using whatever empirical and rationalist tools that may be available.

Shannon [61; pp. 215-217] has suggested a three-staged approach for validating a model. The first stage, primarily rationalistic, requires the reconciliation of model structure at the component level

to observation and to theory. The second stage is related to the first in that component validation is emphasized, but the empiricist's approach is now assumed by the analyst. The third and final stage of Shannon's validation procedure makes use of the pragmaticist's perspective, and the input-output transformations are examined using whatever approach (empirical or rationalistic) is necessary. In reality, Shannon's scheme for testing model validity is not new [ 77.], but his structuring of the process in such detail is. The best test of any validation process is that the resulting model is used confidently by someone aware of both its capabilities, its limitations and its weaknesses.

For the model of the CJS, Shannon's staged approach to model validation is followed. For the first stage, however, nothing more will be said. The description of the model in Section 4.2 and its implementation in Section 5.1 contain the necessary description and justification of the component's assumptions and behaviors. In addition, the final sections of Chapter III justify the structure of the plea bargaining component of the model, so nothing more is required for this stage of validation.

#### 5.3.1 Component Validation

Of the second and third stages of validation, the second is perhaps the easiest for this model. As part of his dissertation, Rhodes [57] investigated the validity of his model of plea bargaining using regression analysis on data from U.S. and Minnesota District Courts. Thus, Rhodes empirically validated the plea bargaining mechanisms used in this thesis. To validate these mechanisms as they are implemented

in the simulation model (cf., Section 4.2.4), three runs of the model are made under the following scenarios.

1. The Constrained Model implements the  $r = 2.5\%$  annual resource growth constraint defined by equations 5-4 and 5-5.
2. The Basic Plea Bargaining Model, often referred to as the Basic Model, implements the resource constraint in 1 above; however, it also requires that the prosecutor respond to the length of the pre-trial delay as described in Section 4.2.4. The baseline queue length is assumed to be  $Q_0 = 10$  for equation 4-5.
3. The Subsidy Model is the Basic Plea Bargaining Model with an  $s = 10\%$  increase in the prosecutor's budget implemented during the first year of experimental operation (i.e., during the 21<sup>th</sup> year of simulation); thus,  $B_{t,k}$  is defined by equation 5-6.

These three policies shall together be referred to as the primary policy set.

The effect that each of these policies has on the length of the pre-trial queue (Boxes 37 and 39) is shown in Figure 4. As expected, the pre-trial queue hovers nominally at a length of 10 for the Basic Plea Bargaining Model as well as for the Subsidy Model. Note, however, that in either case the prosecutor over-responds because of his lack of foresight. When the prosecutor's budget is also increased by 10% as in the Subsidy Model, an oscillating pattern is developed in the queue length because of the conflicting goals of the prosecutor's first and second decisions. When his first decision increases the queue, the second

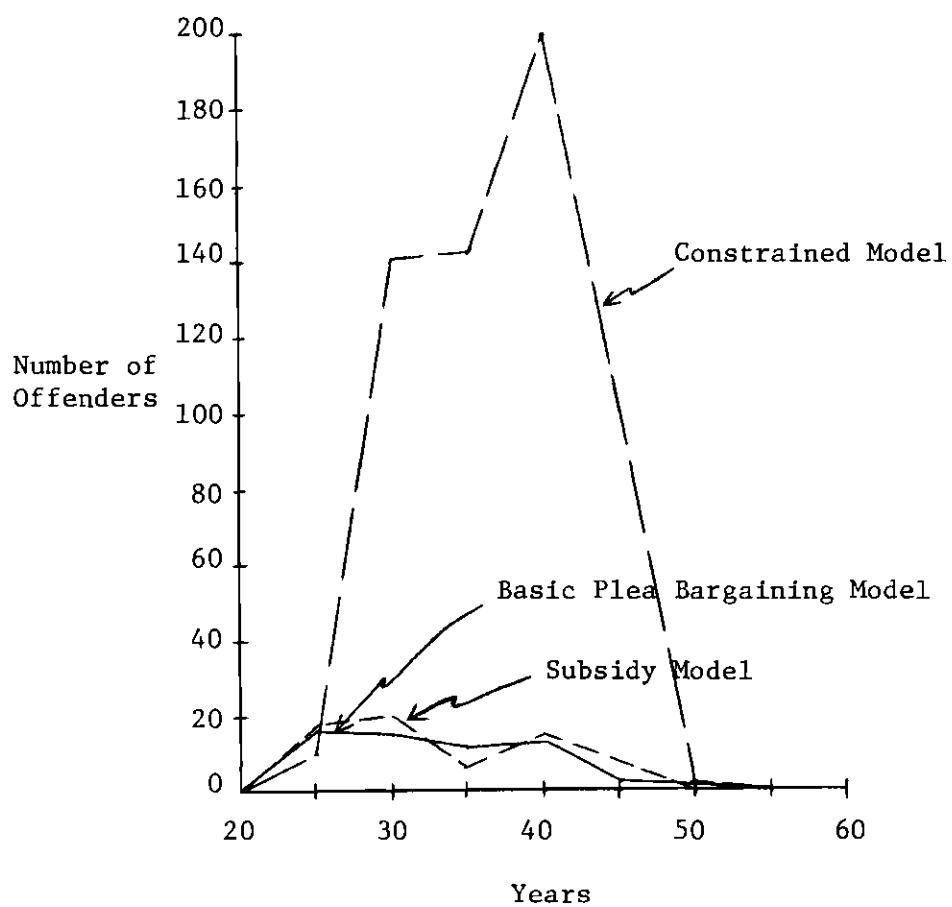


Figure 4. The Superior Court Pre-Trial Queue Length for the Primary Policy Set

simultaneously attempts to reduce it after some stochastic delay time. This delay causes the oscillations in the pre-trial queue length.

With the primary policy set having been validated with respect to the pre-trial queue, the next step is to verify that the remainder of the model responds to these policy variations as it should. As an example of how the validation process has proceeded for the other CJS components, the recidivism delay boxes are examined. Displayed in Figure 5 are the effects that the primary policy set has on the numbers of free recidivists awaiting re-arrest at Boxes 19, 47, and 48. The number at Box 19 is relatively constant between policies because the flow of juveniles changes little when superior court parameters are changed. The number of recidivists at either Box 47 or Box 48, however, does change from one policy to the next. In the figure, the short dashes represent the Constrained Model, the solid line represents the Basic Plea Bargaining Model, and the long dashes plot the Subsidy Model's results. Comparing the responses in Figures 4 and 5, it is clear that the Basic and the Subsidy models are behaving as they should. In going from the Constrained to the Basic Model for the period from year 20 to year 45, the Basic Model forces the release of offenders in order to reduce the length of the pre-trial queue. After year 45, the drastic reduction in the pre-trial queue already experienced in the Constrained Model requires more offenders to be prosecuted, thereby increasing the number of recidivists at Box 47 and at Box 48.

The Subsidy Model plots in Figure 5 also demonstrate the behavior described earlier in Figure 4. The graph for Box 48 demonstrates the same oscillating behavior witnessed earlier; the graph



for Box 47, however, does not. The reason for this difference is that the delays until Box 47 is realized dampen this response considerably. Beyond about the 45<sup>th</sup> year, the number of recidivists at both boxes begins to grow as in the Basic Plea Bargaining Model.

The remaining components of the CJS model have not been validated from the empiricist's perspective; however, the internal consistency of the model as witnessed during the validation of the several responses to the primary policy set is reassuring. Because of this reassurance and the hypothetical nature of the experimental data and of the resource and cost components, further empirical validation of the model's components seems unnecessary.

### 5.3.2 Input-Output Validation

Validating the input to output transformation is described here rather briefly. Because of the several assumptions required in gathering the data, rather than a vigorous analysis of the output vis-à-vis observed system responses, only a few important transformations are discussed. The emphasis of this section is on the output's consistency with observed behavior, not on the exact duplication of real world phenomena. To ensure that the behavior of the model is not unstable, i.e., extremely sensitive to basic assumptions, an appraisal of policy feasibility and model stability is given in Chapter VI, Sections 6.1.2 and 6.2.2.

Career Arrests. One of the output measures which is of particular interest in this analysis is the recidivism rate for each criminal, i.e., the average number of arrests during a criminal career. Plots of these

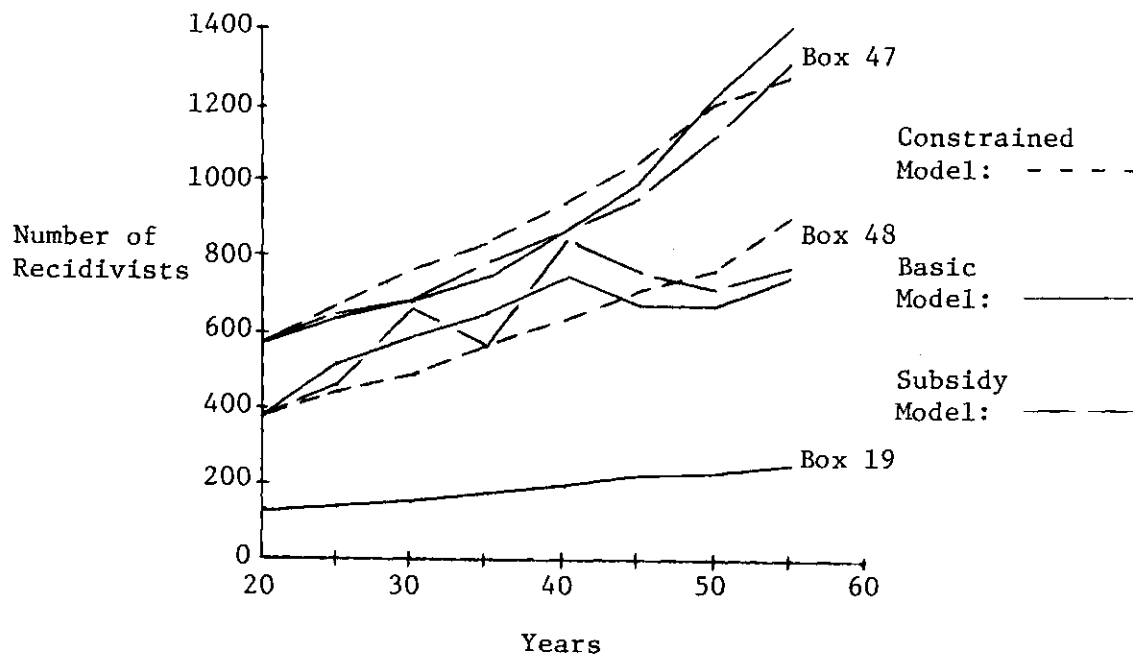


Figure 5. The Number of Free Recidivists for the Primary Policy Set

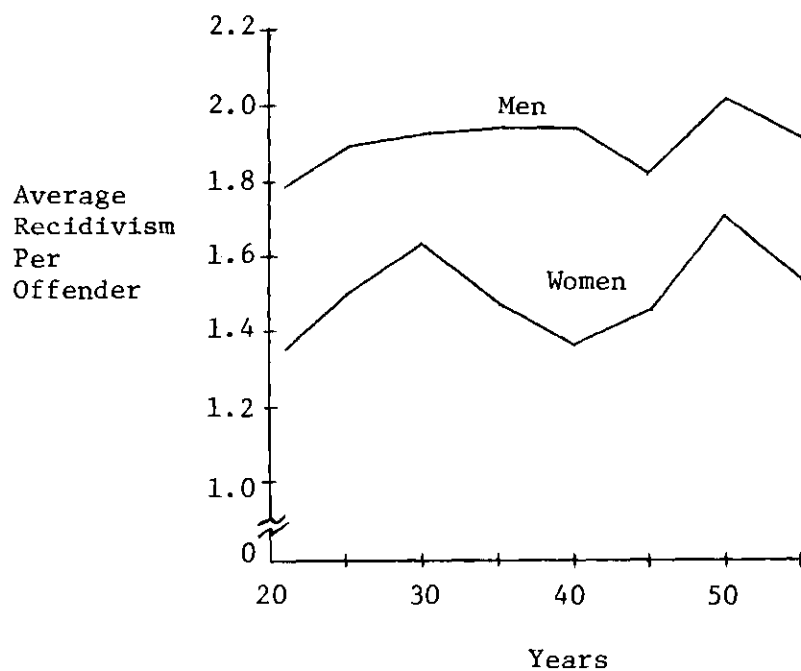


Figure 6. Time Series of the Number of Arrests Per Offender for the Basic Plea Bargaining Model

time series for male and female offenders in Figure 6 show that the duration of the initialization period is at least long enough for these series to stabilize. Table 20 summarizes the average number of arrests per criminal career of a nationwide sample of offenders collected by the FBI [29] as well as comparable results from the Basic Plea Bargaining Model. The difference between the two sources is significant. The magnitude of the simulated statistic is approximately one-third to one-half that of the national sample. In addition, ranking the categories does not ameliorate any differences in the two sources. Part of this difference can be explained by the fact that the national survey gives a snapshot of the recidivism probabilities used in the CJS model and of the number of career arrests; another explanation is that the recidivism probabilities are not time invariant. Perhaps, the more reasonable explanation, however, is that 24% of the male and 12% of the female offenders die in the CJS model before their criminal careers would naturally end according to the stochastics involved. Although data is not available to support or refute either representation of the criminal career, the reason for the high death rates is caused by the exponential assumption of the remaining lifetime of an offender (cf., Section 5.1.1 "First Offender Attributes"). Regardless of this apparent inconsistency, the exponential assumption will not be changed; however, before the model is ever used for policy analysis, this issue must be resolved. Note that in Figure 7, the distributions of the number of offenses committed during male and female criminal careers appears to be exponential. This result agrees with the contention of Avi-Itzhak and Shinnar [5] and their successors, the analytical model-builders.

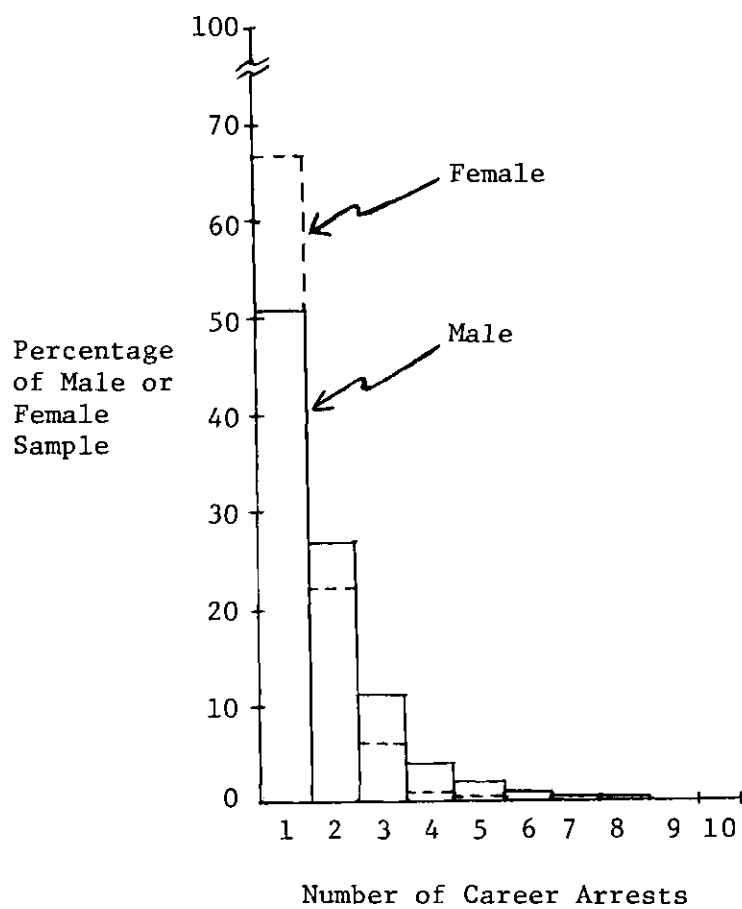


Figure 7. Distributions of Career Arrests for Male and Female Offenders

Table 20. Comparison of Empirical and Model-Generated Number of Arrests During a Criminal Career

Last Crime Committed	UCR: Career Arrests	Model: Male Arrests	Model: Female Arrests
Homicide	4	1.74	1.32
Robbery	5	1.58	1.46
Assault	3	1.59	1.34
Burglary	4	1.53	1.25
Larceny	3	1.91	1.35
Auto Theft	5	2.35	2.05
Rape	3	2.71	2.45
AVERAGE	4	1.90	1.45

Career Criminal Cost. Another important output measure is the career criminal cost. To date nothing conclusive has been derived concerning this measure, but for CJS modeling it is ideally suited for cost optimization. Figure 8 shows time series of the career criminal cost of both male and female offenders. Although these series do have a large variance, their means are essentially constant. This is particularly encouraging since it verifies that the initialization period is at least as long as necessary to remove the transient responses (see Section 5.2.2). The fact that these series are constant in the face of the rising annual CJS cost (also shown) is further verification of the models internal consistency. The total annual cost is rising because of the increases in the virgin and recidivist arrest rates.

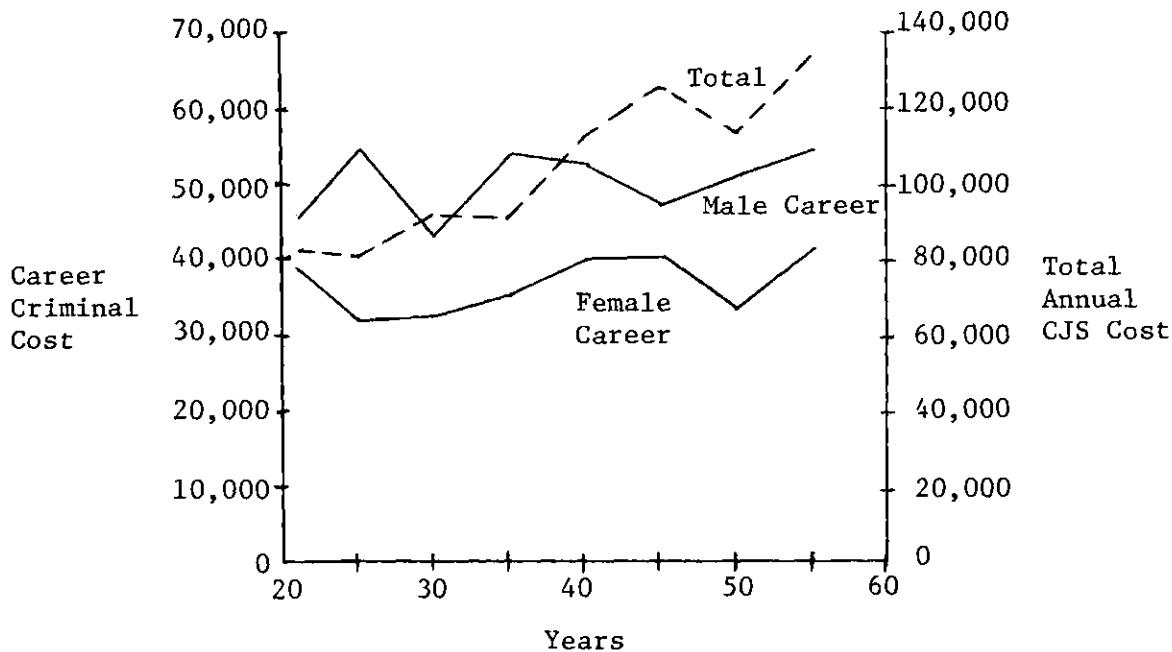


Figure 8. Time Series of Career Criminal and Total Annual CJS Costs for the Basic Plea Bargaining Model

The expected values of the career criminal cost are approximately \$49,619 for men and \$36,697 for women for the Basic Plea Bargaining Model. These measures will of course change from one run to the next and, as described in the following chapter, they will be used as a performance measure in experimenting with plea bargaining.

CJS Resource Cost. One input-output comparison that can be made very easily deals with the distribution of costs in the system. Remember, in Table 19 that estimates of the cost per offender per year were derived for each of the ten resource categories. Using the Kolmogorov-Smirnov goodness-of-fit test, the distribution of these costs can be compared to the percentage contribution to the total CJS

cost of each of the resources for any single execution of the model. The percentage contribution of each resource  $k$  to the total operating cost of the Basic Plea Bargaining Model is shown in Table 21 as  $F_k(A)$ ,

Table 21. Validation of the Cost Model Using the Kolmogorov - Smirnov Goodness-of-Fit Test.

$k$ Resource	$A'_k/1000$	$A''_k = \frac{A'_k}{\sum_k A'_k}$	$F_k(A)$	$\sum_k A''_k$	$\sum_k F_k(A)$	$ D_k $
1	\$ 9.25	.122	.179	.122	.179	.057
2	25.75	.339	.116	.461	.295	.166
3	4.26	.056	.069	.517	.364	.153
4	5.04	.066	.086	.583	.450	.133
5	3.40	.045	.061	.628	.511	.117
6	6.52	.086	.118	.714	.629	.085
7	8.36	.110	.149	.824	.778	.046
8	9.64	.127	.156	.951	.934	.017
9	1.21	.016	.031	.967	.965	.002
10	2.45	.032	.034	.999	.999	0
TOTAL	75.88	.999	.999			

while the empirical (input) values of the cost per resource year are shown as  $A'_k$ . The statistic,

$$|D_k| = \left| \sum_k A''_k - \sum_k F_k(A) \right| ,$$

is computed for each resource  $k$ . According to the Kolmogorov-Smirnov test, if

$$D = \max_k |D_k| \geq d_\alpha$$

then reject the hypothesis that the observed distribution cost is equal to the actual cost distribution. The computed value of  $d_\alpha$  for ten observations (each resource type represents one observation) and  $\alpha = .20$  is .322. Since  $D = .166$ , the hypothesis is not rejected and the cost model is accepted for this particular run.

The significance of this result is important as it shows that the method of initializing the resource and cost components of the model, the distribution of resources to the processors, and the 35-year run length together provide a reasonable cost model for the CJS. Although this test does not validate the magnitude of the costs, it does show that the estimate of costs and the usage rate per offender are satisfactory for this run length. Since the actual total cost depends upon the virgin and recidivism crime rates, little more than internal validity is required for the total cost to be validated and this fact was demonstrated earlier. Thus, the cost model is a reasonable approximation.

#### 5.4 Summary

The purpose of this chapter has been to describe the empirical data used to experiment with the model of the CJS, to initialize the model so that these experiments can be performed, and to discuss the validity of the model so that its limitations can be considered in evaluating the experimental results. Each topic has been covered in succession and the model, despite some limitations in the data, seems to pass several tests of internal validity. The following chapter reports on these experiments with the plea bargaining model.



## CHAPTER VI

### ANALYSIS OF PLEA BARGAINING STRATEGIES

#### 6.0 Introduction

With a fully implemented and validated model in hand, the next and perhaps the most important step in modeling is the design and analysis of experiments using the model to draw inferences about the behavior of the actual Criminal Justice System. The particular experiments to be conducted examine several policy scenarios dealing with the factors sited in Chapter III as having a significant impact on the outcomes of plea bargaining. Initially, the pre-trial delay is allowed to impact the plea bargaining outcome for offenders in the system; the effect that this response has on the average career criminal cost and on recidivism is ascertained. Because it is believed that the size of the pre-trial delay will always serve to regulate plea bargained outcomes, this mechanism is retained in the model for the runs in which case-specific information impacts the plea bargaining decision process. The case-specific information which is available to the prosecutor is alternately the severity of an offender's most recent crime and the number of arrests that have occurred during an offender's criminal career. The effect that the case-specific information has on the plea bargaining disposition is formulated in Sections 3.2 and 3.3 and its implementation in the plea bargaining model has been discussed in Section 4.2.2. An additional factor is

considered to impact the plea bargaining decisions. An increase in the prosecutor's budget (the Subsidy Model) is also a factor in the quasi-experimental design of this chapter.

Although the proposals developed in this chapter are not an exhaustive treatment of alternatives to current plea bargaining policy, it should be emphasized that the purpose here is to examine policy scenarios which impact the cost of processing a career criminal and which change the recidivism rate; however, this analysis is one example of the potential that the simulation approach has for the evaluation of CJS policy. The quasi-experimental design used approaches the type of design that might be used in actual evaluations; the analysis of the data and the sample output displayed demonstrate how the information generated from a simulation model of the Criminal Justice System can be useful in performance evaluation studies.

### 6.1 The Experimental Design

The effect on plea bargaining of having either the severity of the most recent offense or an offender's previous arrest history is the same according to Section 3.3.2. If this information is available to the prosecutor prior to his deciding to prosecute a case, then the offender who has committed the most severe offense and who has been arrested several times in the past is more likely to be prosecuted than a first offender who has committed a less severe crime. Intuitively, such a priori information affects the offender's convictability,  $\phi_1$ . The bigger  $\phi_1$  is, the greater is the likelihood that a case will be prosecuted. For the second plea bargaining decision, whether or not

a defendant pleads guilty, the large  $\phi_i$  offender is more likely to plead guilty since doing so almost guarantees him sentencing leniencies through charge reduction over a trial conviction. This result assumes that the prosecutor's caseload is excessive and that he can spend only a fixed amount on cases that go to trial and a different, but constant, amount on cases where a guilty plea is achieved. (See Section 3.2.)

This effect that a priori information has on plea bargaining is considered the normative response. That is, the above outcomes are expected if the prosecutor is not specifically directed by an "optimizing" policy structure. The purpose of this section is to describe candidate policies to be tested and to explicitly define the performance criteria to be used for these tests. The policies to be tested are each compared to the Basic Plea Bargaining Model described in the previous chapter, Section 5.3.1. This Basic Model is assumed to be the prosecutor's normal response when case-specific a priori information is not available.

#### 6.1.1 Performance Measures

The objective of this analysis as stated once before is to simultaneously reduce recidivism and the cost of processing offenders. Because of the nature of a discrete event simulation model, both of these measures may be analyzed from the viewpoint of the individual offender. Thus, the career criminal cost, defined earlier as the total CJS cost of processing an offender during his entire criminal career, is an excellent choice for a performance measure. In addition, the observed number of arrests during a criminal career is also an

excellent performance criterion. For these experiments, time series of the average number of arrests and of the average career criminal cost of those criminal careers which ended during time  $t$  are recorded; however, as it happens that these series are stationary in their means (cf., Figures 6 and 8), the time series may be replaced by their averages without considerable loss of information. The objective of this analysis, then, is to simultaneously minimize the average number of offenses during a criminal career and the average career criminal cost; a related problem requires the minimization of the total CJS cost over the planning horizon (assumed equal to the run length). Since there is not any one best answer, both of these problems are addressed.

One difficulty with trying to optimize the CJS using the recidivism and CJS cost measures is that they are inversely related. A policy that reduces either the CJS cost or the career criminal cost may be doing so by prematurely releasing defendants and thereby increasing the rate of recidivism. Conversely, a policy which increases either the CJS cost or the career criminal cost is undoubtedly either routing offenders deeper into the CJS (i.e., through the courts and corrections) or increasing their sentences. Thus, a definite trade-off exists between cost on one hand and recidivism on the other.

However, there should also exist a set of policies for which a "social" optimum exists. Such a solution can be determined by converting the average number of arrests per criminal career into an expected social cost (in dollars) that society endures beyond the normal CJS costs when an offender commits a crime. Define the social cost of

a single crime as  $\gamma$ . The expected cost to society of a criminal career under experimental policy  $v$  is,

$$e_v(\gamma) = \gamma \beta_v + \bar{c}_v \quad (6-1)$$

where  $\beta_v$  is the average number of arrests during a criminal career that is observed under policy  $v$ , and  $\bar{c}_v$  is the average career criminal cost for policy  $v$ . Thus, with the appropriate selection of  $\gamma$ , a social optimum may be found by choosing  $v$  such that

$$e^* = \underset{v}{\text{minimize}} \left\{ e_v(\gamma) \right\} . \quad (6-2)$$

For this study,  $\gamma$  is chosen initially to be \$10,000.

#### 6.1.2 Policy Feasibility

Another performance measure not yet discussed is related not to optimization specifically but to policy feasibility. In Chapter V, it was decided that only those CJS resources which are directly associated with plea bargaining (namely, the prosecution and the superior court) would be constrained for these experiments and that all other resource levels would be unconstrained. This action was taken in order to not complicate the analysis of policies in which queues develop which have no meaning in reality. Furthermore, not constraining the other eight CJS resources allows a reasonable amount of gradual expansion to take place without the complications of adding a fixed amount of capacity at one instant.

Feasibility of the activity levels of each of the remaining processors in the CJS network, then, must be a pre-requisite for an

optimal policy scenario. However, because of the diminutive level of activity of all other CJS processors in comparison to that of the male prisons (cf., Figure 9), only the latter will be examined for policy feasibility. The criterion for policy feasibility, therefore, requires that an imaginary upper bound be placed on the prison population. This upper bound,  $(UB)_t$ , is a function of the level of activity at time  $t$  in the prisons for men of the Basic Plea Bargaining Model:

$$(UB)_t = (1 + \rho)B_t \quad (6-3)$$

where  $\rho$  is the percentage tolerance allowed on the prison population and  $B_t$  is the number of male prisoners at time  $t$  from the Basic Plea Bargaining Model. Thus, an infeasible policy is one whose male prison population exceeds  $(UB)_t$  at any point during the simulation. The tolerance  $\rho$  is assumed to be 25%.

From Figure 9, it is clear that the current feasibility criterion is not violated for either the Constrained or the Subsidy Models. Hence, the policies represented by these two alternatives are feasible. If, on the other hand, the activity levels of other corrections processors were examined, a similar bound on their activity levels might cause an alternative to be rejected as infeasible. Take the case of the male jail population in Figure 9. An upper bound of

$$(UB)'_t = 1.25 B'_t ,$$

where  $B'_t$  is the activity level at time  $t$  for the Basic Model, would cause the Constrained Model to be rejected.

The reason the Constrained Model in Figure 9 is not infeasible

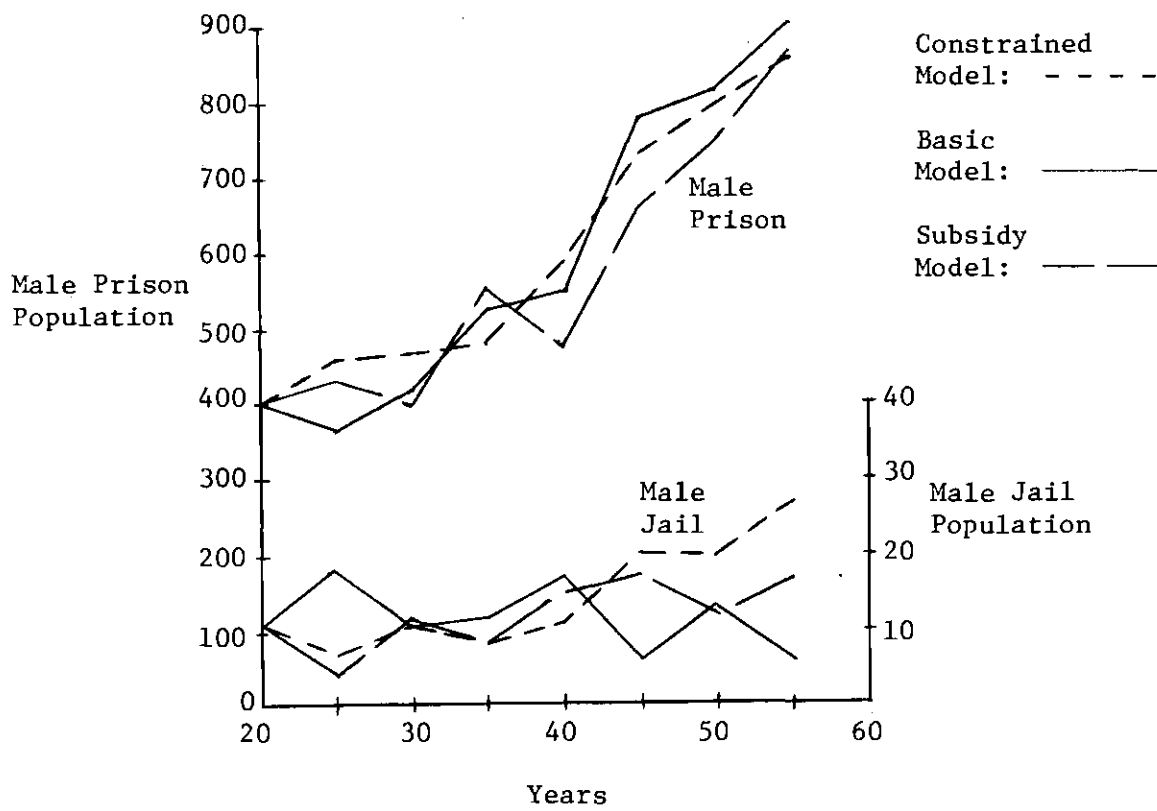


Figure 9. Male Prison and Jail Populations for Primary Policy Set

is that the increase in the male jail population is accompanied by a decline in the male prison population, and this reduction in the prison population entirely off-sets the increase in the jail population. Although the counter-balancing of increases and reductions in the Corrections Subsystem will not always net out to a reduced convict population, whenever the prison population drops an increase is felt in the jail level because of the forces at work in the model. Some preliminary analysis of recidivism shows that the rate of recidivism does not change dramatically over the planning horizon, so a change in the corrections populations must be attributed to the court subsystem; however, since the sentencing model does not change, the plea bargaining apparatus must cause the change in these population levels. Thus, an increase in the prison population is accompanied by a decline in the jail population, and vice versa. Because prison sentences are considerably longer than jail sentences, a decrease in the prison population will cause a smaller increase in the jail population, whereas a decrease in the jail population will cause a much higher increase in the prison population. As a result, the prison population size is the better predictor of policy feasibility since the only other increase in the corrections population would be precipitated by a general increase in the conviction rate which would also increase the size of the prison population.

As for the non-correctional processors, placing a feasibility constraint on them would have little effect. The operation of the Juvenile Justice Subsystem is essentially independent of the plea



bargaining alternative chosen. The court and prosecutor processors, meanwhile, are protected from infeasible activity levels by the prosecutor's continual response to the pre-trial delay. Preliminary analysis of the pre-trial detention processors shows activity levels far below the male prison level (30 versus 900); thus, the male population seems to be the best criterion for policy feasibility. This issue will be further explored along with the other performance measures during the presentation of the results of the simulation experiments.

#### 6.1.3 Plea Bargaining Scenarios

The objective for this study of plea bargaining alternatives is the simultaneous reduction in recidivism and cost with respect to the entire CJS and the statistics of the average offender. Although the response of plea bargaining to increases in an offender's convictability when a priori information is available is the same regardless of the type of information available (Table 3), the cost of each is not. For the severity of an offense, such information is usually available to the prosecutor from police reports. Thus, acquisition of the severity of a crime does not increase the cost of processing a defendant. Acquiring the number of times that an offender has already been arrested, however, does cost the CJS for the maintenance, storage, and acquisition of an offender's arrest records. Thus, such information does require additional capital outlays. Two questions immediately arise which are worth examining using a simulation model:

1. Which type of information produces the desired responses of reduced recidivism and costs, and

2. Does the extra cost of the information retrieval system required for acquiring the arrest histories of offenders outweigh the benefit of having such information available to the prosecutor?

In Chapter III, the "normative" response of plea bargaining to a priori information was given. That is, those responses are expected unless new policy is established. Suppose that a new policy is implemented that requires the prosecutor to not allow the higher convictability ( $\phi_i$ ) defendants to negotiate a plea. To compensate, the lower  $\phi_i$  defendants must be convinced to plead guilty. Such a scenario is desirable from the point of view that the higher the crime severity of the most recent offense and the more an offender has been arrested, the greater the likelihood of a court trial and of a longer period of incapacitation. If the ability to convince the low- $\phi_i$  offender to plead guilty is assumed, then this scenario would produce interesting results that should be examined carefully. This scenario is denoted the "special" response to a priori information to differentiate it from the normative response of Chapter III.

To implement the special response to a priori information in the simulation model, recall that in Chapter IV, weighting functions were developed to alter the branching probabilities of Boxes 23 and 32 and of Node 30. Implementing this special response to plea bargaining merely requires that the weighting function for Box 32 (the arraignment hearing) be altered. The weighting function (at time  $t$  for offender  $i$  who commits crime  $j$ ) which replaces equation 4-11 for the special

response is

$$W''_{ijt} = (G_t H_t) / (I_i J_i) , \quad (6-4)$$

where  $G_t$ ,  $H_t$ ,  $I_i$  and  $J_i$  are defined in Chapter IV. Thus, the net result is that the reciprocals of the two information factors is assumed for the special response to plea bargaining.

Recapitulating, the following effects should be tested:

1. The normative response to the number of criminal arrests in an offender's career (his arrest record or history),
2. The normative response to the severity of the most recent crime committed,
3. The special response to an offender's arrest record,
4. The special response to crime severity.

The interaction of these alternatives will not be tested. Since it seems likely that under all circumstances the prosecutor must ration trials whenever the pre-trial queue becomes large, the mechanism described in Chapter V and called the Basic Plea Bargaining Model is maintained throughout these experiments. Thus, any output must be considered to be the result of the specified effect as well as the effect of the prosecutor's response to pre-trial delay.

For each of these four scenarios, additional tests can be made on the interaction between these effects and an accompanying increase (assume 10%) in the prosecutor's budget (i.e., the Subsidy Model described in the previous chapter). Thus, the total number of scenarios to be tested is  $4 \times 2 = 8$ :

1. Two runs of the Basic Model for the normal and special responses to an offender's arrest history,
2. Two runs of the Basic Model for the normal and special responses to the severity of an offender's crime,
3. Two runs of the Subsidy Model for the two responses to an offender's arrest history,
4. Two runs of the Subsidy Model for the responses to the severity of the offender's crime.

The results for the Basic and Subsidy Models without a priori information are also reported for completeness. Thus, the results for ten runs shall be reported in the analysis of this quasi-experimental design.

#### 6.1.4 Variance Reduction

Because of the time limitations, an analysis of the most appropriate set of variance techniques for this model has not been attempted. One technique which is often resorted, however, is to use a set of random numbers common to each experimental run [30]. This technique has been used here with an unknown degree of success.

### 6.2 Experimental Results

The ten scenarios described in Section 6.1.3 have been executed using the GNS model described in Chapter IV and implemented in Chapter V. The following naming conventions for these scenarios are assumed. The Basic Plea Bargaining Model, called the Basic Model, assumes that the prosecutor adapts to the length of the pre-trial delay only; the Subsidy Model assumes this same response to the pre-trial queue but accompanied by a 10% increase in the available number of prosecution servers at the

Table 22. Simulated Performance Measures

Experimental Run	Total CJS Cost (\$ x 10 <sup>9</sup> )	Average Male Recidivism (No. Offenses)	Average Male Career Criminal Cost	Average CJS Cost Per Male Arrest	Average Social Cost Per Male Career Criminal
1. Basic Model	\$1381.6 (1.24)	\$1.906 (-.76)	\$49,619 (1.67)	\$26,157 (1.14)	\$68,679 (2.02)
2. -Normal Severity	1296.5 (-.60)	1.979 ( .41)	46,560 (-.48)	23,699 (-.49)	66,350 (-.45)
3. -Special Severity	1283.5 (-.88)	2.018 (1.05)	45,800(-1.01)	22,812(-1.08)	65,980 (-.84)
4. -Normal History	1379.7 (1.20)	1.857(-1.55)	48,910 (1.17)	26,550 (1.40)	67,480 ( .75)
5. -Special History	1290.2 (-.74)	1.956 ( .05)	46,914 (-.23)	24,142 (-.20)	66,474 (-.32)
6. Subsidy Model	1376.1 (1.12)	1.919 (-.55)	48,406 ( .82)	25,609 ( .77)	67,596 ( .87)
7. -Normal Severity	1304.1 (-.43)	2.004 ( .82)	46,256 (-.68)	23,389 (-.69)	66,296 (-.51)
8. -Special Severity	1288.1 (-.78)	2.038 (1.37)	46,294 (-.67)	22,769(-1.11)	66,674 (-.11)
9. -Normal History	1377.7 (1.16)	1.858(-1.53)	48,525 ( .90)	26,467 (1.35)	67,105 ( .35)
10. -Special History	1264.7(-1.29)	1.995 ( .68)	45,154(-1.47)	22,825(-1.07)	65,104(-1.77)
Expected Value	1324.2	1.953	47,244	24,442	66,774
Standard Deviation	46.1	.062	1425	1506	940
Simple Correlation to Male Recidivism	-.877	1.000	-.870	-.975	-.660

start of the experimental epoch. The normative response to crime severity is labeled "Normal Severity" while the normative response to an offender's arrest record is labeled "Normal History." These normative responses were described in Chapter III. The special responses to a priori information, described in Section 6.1.3, are distinguished by the terms "Special Severity" and "Special History" for the runs in which the crime severity and the arrest record of an offender are available to the prosecutor.

#### 6.2.1 Performance Optimization

The results of the performance measures for each of the ten runs of the model are shown in Table 22. Whereas, the total CJS cost statistic is determined over both the initialization and the experimental periods of the simulation, the remaining statistics are computed exclusively over the 35 years of the experimental period. In addition, for ease of interpretation, each statistic is accompanied in parentheses by its normalized equivalent. That is, define  $\Xi_{\ell, \nu}$  as the  $\ell^{\text{th}}$  statistic in Table 22 for run  $\nu$ . The normalized value of  $\Xi_{\ell, \nu}$  requires the linear transformation

$$\Xi'_{\ell, \nu} = \frac{\Xi_{\ell, \nu} - E_{\ell}(\Xi_{\ell, \nu})}{V_{\ell}(\Xi_{\ell, \nu})^{1/2}}, \quad (6-5)$$

where  $E_{\ell}$  and  $V_{\ell}$  are the expectation and variance operators defined for the  $\ell^{\text{th}}$  statistic as

$$E_{\ell}(\Xi_{\ell, \nu}) = \frac{1}{10} \sum_{\nu=1}^{10} \Xi_{\ell, \nu} \quad (6-6)$$

and 
$$V_{\ell} \left( \Xi_{\ell, v} \right) = E_{\ell} \left( \Xi_{\ell, v}^2 \right) - E_{\ell} \left( \Xi_{\ell, v} \right)^2 . \quad (6-7)$$

Therefore, if  $\Xi'_{\ell, v} < 0$  the statistic  $\Xi_{\ell, v} < E_{\ell} \left( \Xi_{\ell, v} \right)$ ;  
likewise, if  $\Xi'_{\ell, v} > 0$  then  $\Xi_{\ell, v} > E_{\ell} \left( \Xi_{\ell, v} \right)$ .

Increasing the Number of Prosecutors. In Table 22, the total CJS cost statistics point to the Special History Subsidy Model ( $v = 10$ ) as being optimum, while the average male recidivism measure shows the Normal History Basic Model ( $v=4$ ) to be optimum. Further explanation of these two performance measures confirms that a definite negative relationship ( $p = -.877$ ) exists between CJS cost and recidivism. This relationship was anticipated because of the trade-off between reduced recidivism through incapacitation and the cost of attaining greater incapacitation.

It is also easy to see in Table 22 that each Basic Model ( $v=1, 2, 3, 4, 5$ ) has a lower rate of recidivism than its counterpart Subsidy Model ( $v = 6, 7, 8, 9, 10$ , respectively). Increasing the prosecutor's staff by 10%, therefore, increases the expected recidivism rate for each offender. This increase in recidivism results from the build-up in the pre-trial queue. This trial backlog is precipitated by the prosecutor's sending more offenders to the courts even though the court resources have not increased to handle the extra load. Thus, although the prosecutor's staff has increased, the tendency of the pre-trial queue to be longer for the Subsidy Model causes more offenders to be released by the prosecutor before trial and the rate of

Table 23. Expected Differences in Total Male Arrests

$\begin{matrix} v_2 \\ v_1 \end{matrix}$	1	2	3	4	5	6	7	8	9	10
1	0	1095	1680	-735	750	195	1470	1980	-720	1335
2		0	585	-1830	-345	-900	375	885	1815	240
3			0	-2415	-930	-1485	-210	300	-2400	-345
4				0	1485	930	2205	2715	15	2070
5					0	-555	720	1230	-1470	585
6						0	1275	1785	-915	1140
7							0	510	-2190	-135
8								0	-2700	-645
9									0	2055
10										0

Note: This analysis assumes that 15,000 persons comprise the male offender population. Table entries are:

$$\text{Arrests } (v_2) - \text{Arrests } (v_1) \quad .$$



recidivism to be higher than for the Basic Model.

Although the exact number of recidivists who desist in their criminal activities varies from one run to another, approximately 15,000 males desisted during the exponential epoch of each run. Using this estimate of the number of criminal careers who are completed during the 35 year horizon, the expected number of arrests of this population for any run  $v$  is

$$\text{Arrests } (v) = 15000 \beta_v \quad (6-8)$$

The expected increase in the number of arrests by changing from current policy  $v_1$  to policy  $v_2$  is shown in Table 23 for each policy pair. Using this table, several pieces of information can be obtained. Policy  $v = 4$  it seems dominates all other policies since for each  $v_1 = 4$ , the table entries are non-negative while for  $v_2 = 4$ , the table entries are all non-positive. Thus, policy  $v = 4$  has the lowest recidivism rate of these scenarios, but policy  $v = 8$  has the highest recidivism rate of all the alternatives.

In addition, if an analyst is considering increasing a prosecutor's budget by 10%, then by comparing policies  $v_1 = 1$  through 5 with the corresponding policy of the Subsidy Model ( $v_2 = v_1 + 5$ ) it is clear that such a change always increases recidivism. Such increases ranging from a minimum of 15 arrests for  $v_1 = 4$  and  $v_2 = 9$  to a maximum of 585 arrests for  $v_1 = 5$  and  $v_2 = 10$ . The largest difference between any two scenarios occurs for the policy pair  $v = 4$  and  $v = 8$  (the dominating policies). At 18.1% of the total number of offenders who desisted during the experimental period,

the savings in crimes can be quite significant, 78 index offenses per year in the case of the transition from policy 8 to policy 4.

The increase in the recidivism rate for the Subsidy Models over the Basic Models is further demonstrated by dividing the average career criminal cost of the male offender for each model by its corresponding average recidivism rate. The result may be interpreted as the average CJS cost per male arrest (see Table 22). This cost is smaller in every instance for the Subsidy versions ( $v = 6$  to 10) of the Basic Plea Bargaining Models ( $v = 1$  to 5), substantiating the conclusion that recidivism is increased for the Subsidy Models by reducing the incapacitation effect of the CJS.

Responding to A priori Information. The question now arises: What other information can be gleaned from these performance measures? Once again looking at total CJS cost and recidivism, the special responses to a priori information have in all cases a lower total CJS cost at the expense of higher recidivism than the normative responses to the same type of information. This effect is not dictated by the response to a priori information; rather, it is overwhelmed by the prosecutor's response to pre-trial delay. Since the special response to a priori information requires that the high  $\phi_1$  offender not be allowed to negotiate a plea (or at least reduce the likelihood of his doing so), if there is a greater number of high  $\phi_1$  offenders being prosecuted, the pre-trial delay will increase as more offenders are routed to the longer service time processor, the court trial. This is undoubtedly what happens when the prosecutor has an offender's arrest record because the average rate of recidivism is higher for men than

for women. The latter is only 13% of the offender population. With more men going to trial than for the normal response to an offender's arrest record, the prosecutor's response to the pre-trial queue rations the courts more carefully and more offenders with lower  $\phi_i$  are released before trial.

When the severity of an offense is available to the prosecutor, however, the formulation of the model causes all offenses but murder, assault and rape to be less severe than the norm. For the normal response, offenders who commit the less severe offenses are increasingly more likely to negotiate guilty pleas, whereas those offenders who committed murder, assault or rape are more likely to be sent to trial. For the special response, however, the murder, rape and assault cases are more likely to plead guilty while the other cases go to trial. This, of course, occurs unless the pre-trial queue also impacts the process. When this happens for the special response, since there are more burglary, larceny, auto theft and robbery cases than there are murder, rape and assault cases, the pre-trial queue grows until the prosecutor observes the growth and responds by releasing offenders before they are convicted. This action on the part of the prosecutor reduces the total CJS cost while increasing recidivism.

Optimizing Social Costs. From the total CJS cost and the average male recidivism performance measures, it is not clear exactly which policy is a social optimum. The trade-off between CJS cost and recidivism clouds the issue and makes optimization most difficult. Even the average career criminal cost statistic for men demonstrates

Table 24. Ranking Policy Alternatives on the Basis of Career Criminal Social Cost of Male Offenders

<u>Rank</u>	<u>v</u>	<u>Model</u>	<u><math>e_v</math></u>	<u><math>e_v - e^*</math></u>	<u><math>15,000(e_v - e^*)</math></u>
1	10	Subsidy - Special History	\$65,104	\$ 0	\$ 0
2	3	Basic - Special Severity	65,980	876	$13.14 \times 10^9$
3	7	Subsidy - Normal Severity	66,296	1192	$17.88 \times 10^9$
4	2	Basic - Normal Severity	66,350	1246	$18.69 \times 10^9$
5	5	Basic - Special History	66,474	1370	$20.55 \times 10^9$
6	8	Subsidy - Special Severity	66,674	1570	$23.55 \times 10^9$
7	9	Subsidy - Normal History	67,105	2001	$30.02 \times 10^9$
8	4	Basic - Normal History	67,480	2376	$35.64 \times 10^9$
9	6	Subsidy Model	67,596	2492	$37.38 \times 10^9$
10	1	Basic Model	68,679	3575	$53.63 \times 10^9$

Note:  $e_v(\gamma) = \gamma\beta_v + \bar{C}_v$  and  $e^* = \underset{v}{\text{minimum}} \{e_v\}$

where  $\gamma = \$10,000$  is the expected social cost of a single crime,

$\beta_v$  is the average recidivism per male offender,

$\bar{C}_v$  is the average career criminal cost.

an inverse relationship to male recidivism. Thus, other measures must be used to determine a socially optimal policy for plea bargaining.

In equation 6.1, a measure was proposed which combines the cost and the recidivism elements of the CJS performance vector. This statistic, referred to as the social cost of policy  $v$ , adds the expected career criminal cost to the expected cost to society incurred every time an offender is arrested. Thus, the new statistic measures the total CJS cost and the total cost of the crimes committed by offenders over their entire careers. Computing the expected social cost of the male criminal career for each of the policy alternatives, the social optimum  $e^*$  defined by equation 6-2 occurs for  $v = 10$ , the Special History Subsidy Model.

Ranking the policies in Table 24 according to increasing social cost, it is clear that significant savings can be made by choosing the social optimum; the minimum cost between the optimal policy and the next most desirable alternative is  $(e_3 - e^*) = \$876$  per male criminal career. Under the assumption that 15,000 offenders will desist during this 35 year period, \$13.4 million can be saved by choosing the Special History Subsidy Model over the Special Severity Basic Model. Although this savings is only 1.3% of the expected \$989.7 million cost of the latter model, the real savings is realized between the Basic Model, the policy structure currently existing, and the first-ranked model. This savings is \$3575 per male criminal career of \$53.625 million over the 35-year horizon. For the \$1030.2 million total CJS

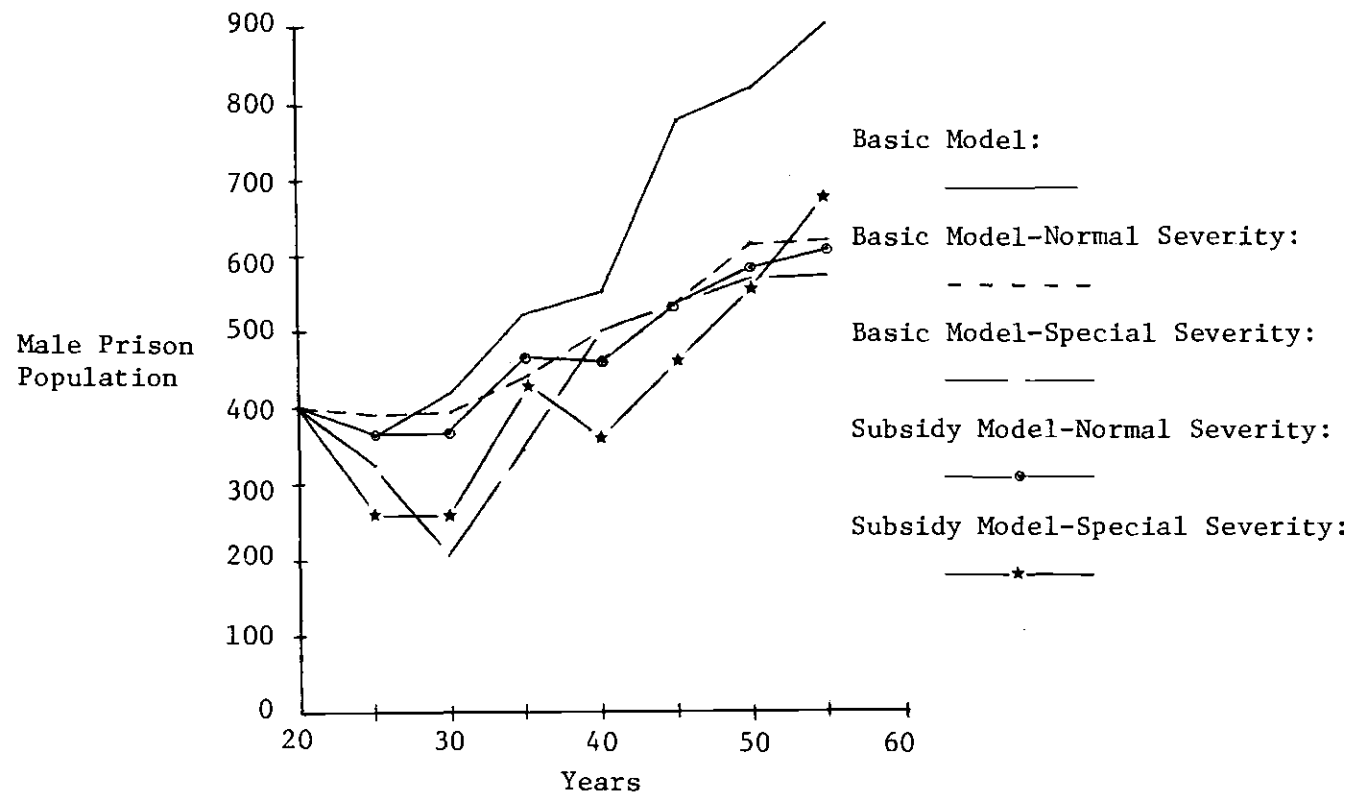


Figure 10. Male Prison Population When Crime Severity is Available to Prosecutor

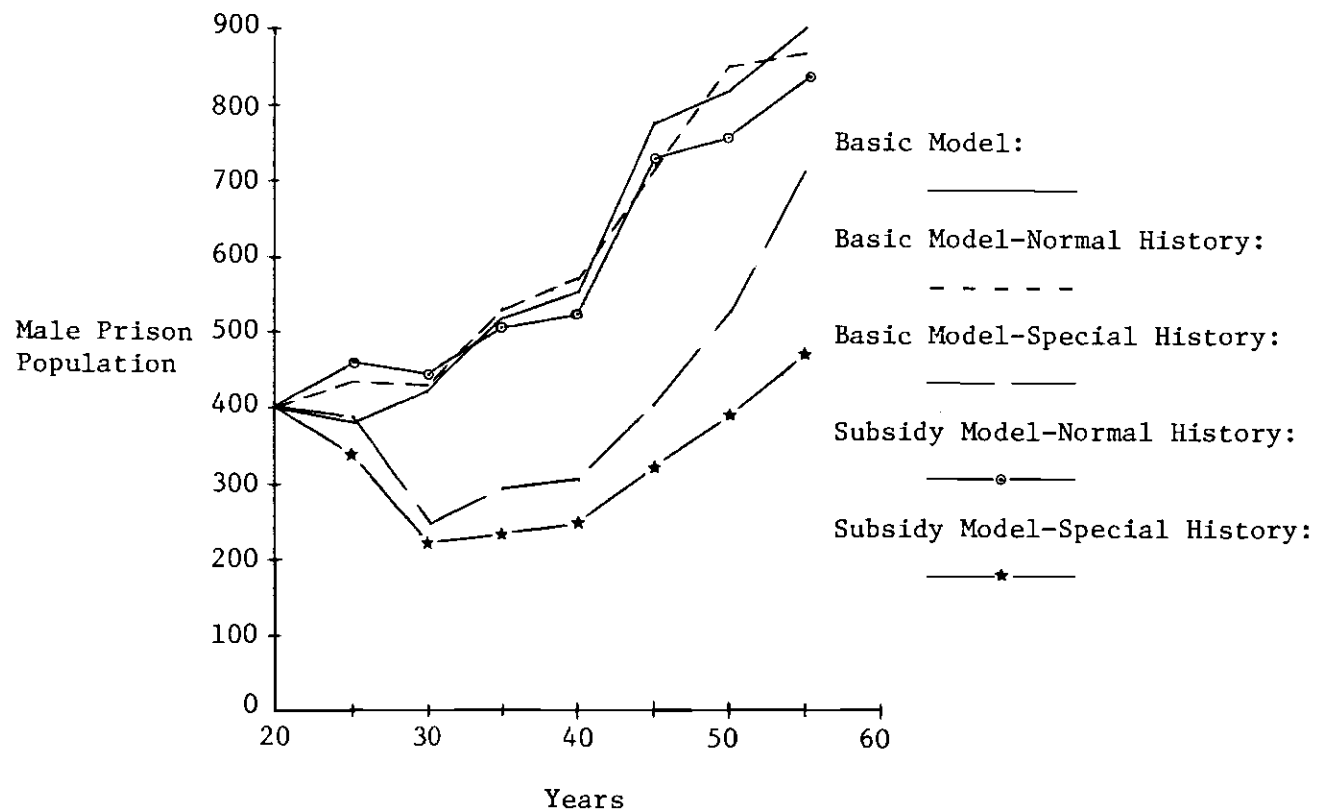


Figure 11. Male Prison Population When An Offender's Criminal Arrest History is Available to the Prosecutor

cost computed for 15,000 desisting offenders, the savings realized in changing from the current policy to that of the Special History Subsidy Model amounts to 5.2% of the total expected cost.

#### 6.2.2 Policy Feasibility

Any policy scenario chosen for possible implementation is tentative until its feasibility has been resolved. The criterion for feasibility established earlier requires that the size of the male prison population must not exceed at any time 125% of the size of the prison population of the Basic Model. To demonstrate the feasibility of all of the policy alternatives to the Basic Model, the size of the male prison population for each scenario is plotted as a discrete time series in Figures 10 and 11. Only two of these time series even approach this feasibility bound, the normative response to an offender's criminal history of both the Basic and of the Subsidy Models. In Figure 11, these near-violations occur during the first ten years of the experimental epoch of the simulation. Thus, even those policies which approach the criterion of infeasibility do so for a short period. The behavior of the Basic Model is such that the male prison population grows rapidly enough that the discrepancies in inmate levels between either run which is suspect and the Basic Model can be viewed as anticipating the growth of the Basic Plea Bargaining Model. Thus, a violation of the feasibility criterion does not actually exist for any of the alternatives shown.

Other important characteristics of the time series in Figures 10 and 11 follow without further explanation.



1. The Basic Model versus the Subsidy Model: The magnitude of the time series of the male prison inmate population is generally larger for the Basic Model than for the corresponding Subsidy Model.
2. The Crime Severity Effect: The normative and the special plea bargaining responses to the severity of an offense for either the Basic or the Subsidy Model force the size of the inmate population to be smaller than that of the Basic Plea Bargaining Model (Figure 10).
  - a. The male inmate populations for the runs of the Special Severity scenario are generally lower than for the Normal Severity Model; however,
  - b. The inmate level of the special response approaches the inmate level of the normal response for the Basic and the Subsidy Models.
3. The Criminal History Effect: The plea bargaining response to an offender's arrest record produces varying results (Figure 11).
  - a. The Normal History responses to the Basic and Subsidy Models yield levels of the male prison population that are essentially the same as the prison population for the Basic Model without a priori information;
  - b. The special response for the Basic Model results in a prison population whose time series resembles that of the Special Severity alternatives.

- c. The Special History Subsidy Model yields a male prison population which is smaller than that of any other scenario at any time.

### 6.2.3 Sensitivity Analysis

The final selection of a policy scenario for implementation in an actual CJS depends, of course, on many factors, some of which are realized in this model. For the many factors which either have not or could not have been adequately modeled, rather than repeat these experiments for a number of factors which are of secondary importance, the sensitivity of the performance measures to parameter changes can be evaluated. Even though such analyses might seem as important, the actual cost of the repeated execution of the simulation model may be prohibitive. For this example, the simulation model required 85,000 words of storage on a CDC Cyber 74 computer (100,000 words available), and it executed using approximately 2 hours of CPU time for each run. Because of the cost to execute this model and the slow turn-around precipitated by the size of the model and the length of each run, examining the effects of several other factors may be prohibited.

A less expensive alternative to conducting experiments on secondary effects, sensitivity analysis on the performance function can yield considerable insight at a significant savings. For example, the social cost function,

$$e_v(\gamma) = \gamma\beta_v + \bar{c}_v ,$$

is a function of the parameter  $\gamma$ , the expected cost to society of each

crime an offender commits. Earlier,  $\gamma$  was arbitrarily set at \$10,000 and the Special History Subsidy Model ( $v = 10$ ) was chosen as the optimal. But it is not exactly clear what value  $\gamma$  should assume, and it would be highly instructive to determine the range of  $\gamma$  over which policy  $v = 10$  is an optimum. In addition, if other policies were to become optimal, knowing the range of  $\gamma$  over which each policy was the optimum would allow a policy-maker some flexibility in choosing  $\gamma$ .

To determine the range of  $\gamma$  for which policy  $v$  is an optimum requires that the extreme points of the convex set defined by  $e_v(\gamma)$  for all  $v$  and  $\gamma \geq 0$  be determined. However, this amounts to finding the non-negative intersection points of  $e_v(\gamma)$  and  $e_{v_0}(\gamma)$  for all  $v \neq v_0$ . Algebraically, this requires setting  $e_v(\gamma) = e_{v_0}(\gamma)$  and solving for  $\hat{\gamma}_{v,v_0}$ , the social cost per crime where policy  $v$  and  $v_0$  have the same career criminal social cost:

$$\hat{\gamma}_{v,v_0} = \frac{\bar{c}_v - \bar{c}_{v_0}}{\beta_{v_0} - \beta_v} \quad (6-9)$$

These results are shown in Table 25. The smallest positive value of  $\hat{\gamma}_{v,10}$  then is the social cost per criminal arrest beyond which  $v_0 = 10$  is no longer optimal. The result is policy 9 at  $\hat{\gamma}_{9,10} = \$24,606$ . Therefore, policy 10 is optimal for  $\$0 \leq \gamma < \$24,606$ . Repeating this operation for  $v_0 = 9$ , remembering that  $\hat{\gamma}_{v,9} \geq \hat{\gamma}_{9,10}$ , the result is that policy 9 is optimal over the range

$$\$24,606 \leq \gamma < \$385,000.$$

Table 25. Determining  $\hat{\gamma}_{v,v_0}$  for the Career  
Criminal Social Cost for Men

$v \backslash v_0$	10	9	4
1	50,168	-22,791	8,020
2	87,875	16,239	23,368
3	-28,087	17,031	23,217
4	27,217	385,000	—
5	45,128	16,438	24,323
6	42,789	1,950	15,177
7	-122,444	15,541	21,503
8	-26,511	12,394	20,889
9	24,606	—	—
10	—	—	—

Finally, repeating this procedure for  $v_0 = 4$ , all values of  $\hat{\gamma}_{v,4}$  are less than \$385,000. Thus, there exist three optimal policy candidates based on the career criminal social cost and the selection of one of these would depend on the actual value of  $\gamma$  for a particular CJS:

$$v^* = \begin{cases} 10 & \text{if } \$0 \leq \gamma < \$24,606 \\ 9 & \text{if } \$24,606 \leq \gamma < \$385,000 \\ 4 & \text{if } \$385,000 \leq \gamma \end{cases}$$

It should be noticed that each of these three policies requires the prosecutor to respond to an offender's arrest record.

The selection of an optimal policy would require that such information be made available to CJS administrators. If the true value

of  $\gamma$  is less than \$385,000, the optimal policy dictates that a 10% increase in the prosecutor's budget (viz, in the number of prosecuting attorneys) be made over the budget of the Basic Plea Bargaining Model, whereas for  $\gamma > \$385,000$  the prosecutor's budget should not be increased beyond current spending levels. In addition, if the true value of  $\gamma$  is less than \$24,606, policy 10 is optimal and the prosecutor should force those offenders who have more extensive criminal records to go to trial (the special response to an offender's arrest record) even though the resulting rate of recidivism is higher for each male offender. If the true value of  $\gamma$  is greater than or equal to \$24,606, however, the repeat offender should be allowed to negotiate a guilty plea in order to reduce the male recidivism rate.

#### 6.2.4 Female Offenders

In examining the results of experiments with plea bargaining, the evaluation in the previous two sections has focused on the male career criminal. This was done primarily because the male offender is such a dominate factor in the generation of crime. From the analysis of those offenders who desist in their criminal careers during the 35 year epoch of the simulation, 87.2% of the total were men. This estimate is not surprising as the percentage of the first offender population which is male varies between 81.5% and 99.0% for the seven index offenses. However, because plea bargaining policy affects the female offender as well as the male, this section is included,

1. To appraise the differences between the male and the female career criminals,

2. To evaluate the effect that each of the proposed plea bargaining scenarios has on the female's career in crime and on the cost of the average career of the female offender, and
3. To re-examine the optimality of those policies cited for the male criminal when the woman's criminal career is included in the performance criterion.

Career Criminal Profiles. Not only are there dramatic differences between the number of male career criminals (approximately 15,000) and the number of female career criminals (approximately 2,200) which desist during the 35-year runs, but other differences which reflect differential CJS treatment and recidivism tendencies exist as well. Specifically, the average recidivism rate for men for the ten runs is 1.953 crimes per criminal career, while the same rate for women is 1.495 crimes per criminal career. The average career criminal cost for men is also significantly greater than that for women. This disparity is partially explained by the differences in the recidivism rates for each sex, but it is also explained by the differences between the average CJS cost per male arrest and the average cost per female arrest. The average CJS cost per female arrest is 9.1% smaller than the comparable figure for men, the average recidivism for women is 23.5% smaller than the rate for men, and the reduction in the career criminal cost for women is 30.1% of that for the male offender. Thus, the expected CJS cost of processing a woman over her entire life is approximately 70% that of any man. This of course is not to say that women are treated less harshly by the CJS; rather, there exists a

Table 26. Simulated Performance Measures for Female Offenders

Experimental Run	Average Female Recidivism (No. Offenses)	Average Female Career Criminal Cost	Average CJS Cost Per Female Arrest	Expected Social Cost Per Female Career Criminal
1. Basic Model	1.456 (-1.18)	\$36,691 (1.67)	\$24,984 (1.44)	\$51,251 (1.70)
2. -Normal Severity	1.492 ( -.09)	32,803 (-.11)	22,515 ( . 16)	47,723 (-.14)
3. -Special Severity	1.528 ( 1.00)	32,490 (-.25)	21,387 (-.43)	47,770 (-.12)
4. -Normal History	1.472 ( -.70)	34,711 ( .76)	23,693 ( .77)	49,431 ( .75)
5. -Special History	1.509 ( .42)	32,321 (-.33)	20,954 (-.65)	47,411 (-.30)
6. Subsidy Model	1.467 ( -.85)	34,919 ( .86)	24,026 ( .94)	49,589 ( .83)
7. -Normal Severity	1.521 ( .79)	33,020 (-.01)	21,700 (-.27)	48,230 ( .12)
8. -Special Severity	1.533 ( 1.15)	29,587 (-1.57)	19,103 (-1.61)	44,917 (-1.60)
9. -Normal History	1.438 (-1.73)	34,504 ( .67)	24,289 (1.08)	48,884 ( .47)
10. -Special History	1.534 ( 1.10)	29,374 (-1.67)	19,470 (-1.42)	44,714 (-1.71)

tendency for women not to recidivate as many times as the male offender and there is a tendency for a women not to cost the CJS as much per arrest as do men. In the model, this last fact can be attributed, to the more lenient sentences that women receive than men.

Performance Optimization, Female Offenders. In Table 26 appears the results for women which corresponds to the run-by-run accounting of the performance factors developed for male offenders that was shown in Table 22. As before, the actual value of each statistic is accompanied by its normalized value in parentheses (cf., equations 6-5, 6-6, 6-7). It was just noted that the expected values of these statistics were all lower for women than for men. It should also be observed that a great similarity exists between the statistics for men and for women. In particular, besides the fact that each statistic is always smaller for women than for men for each run of the same policy scenario, the normalized statistics for men and women differ in sign only for the  $v = 2$  model, the Normal Severity Basic Model. Yet, this disparity occurs for values of the normalized statistic close to zero (the absolute difference is 0.50 for the Career Criminal Cost and it is 0.65 for the average CJS cost per arrest). Therefore, these differences do not demonstrate any radical departures in the handling of each sex for the  $v = 2$  model.

As observed for the male offenders, an inverse relationship exists between the recidivism rate of female offenders, on the one hand, and the cost of processing offenders on the other (Table 27).



Table 27. Summary Statistics for Male and Female Offenders.

	Average Recidivism (Male/Female)	Average Career Criminal Cost (Male/Female)	Average CJS Cost Per Arrest (Male/Female)	Expected Social Cost Per Career Male/Female)
Expected Value	1.953/1.495	47,243.8/33042	24441.9/22212.1	66773.8/47992.0
Standard Deviation	.063/.033	1425.3/2191.7	1505.62/1930.9	940.2/1917.1
Simple Correlation to Male Recidivism	1.000/.915	-.870/-.761	-.975/-.829	-.660/-.711

Because of the difficulty in choosing a policy which results in the minimization of both of these factors, the career criminal social cost statistic, for  $\gamma = \$10,000$  was used for performance optimization in Section 6.2.1. As was the case for male offenders, the minimum social cost for women occurs for policy  $v = 10$ , the Special History Subsidy Model, and the maximum social cost occurs with the Basic Plea Bargaining Model,  $v = 1$ .

Referring now to Table 28, the expected savings in the number of crimes committed by women over the 35 year planning horizon differs greatly from the results for men given in Table 23. Only policy  $v = 10$  dominates all other policies in that the recidivism rate for women is higher for  $v = 10$  than any other alternative.

Performance Optimization, All Offenders. Rather than make the decision about the optimality of one policy scenario over another by

Table 28. Expected Differences in Total Female Arrests

$v_1 \backslash v_2$	1	2	3	4	5	6	7	8	9	10
1	0	79	158	35	116	24	143	169	-39	171
2		0	79	-44	37	55	63	90	-118	92
3			0	-123	-41	134	15	11	-198	13
4				0	81	-11	108	134	-75	136
5					0	-92	26	53	-156	55
6						0	119	145	-64	147
7							0	26	-183	29
8								0	-209	2
9									0	211
10										0

Note: This analysis assumes that 2,200 persons comprise the female offender population Table entries are:

$$\text{Arrests } (v_2) - \text{Arrests } (v_1)$$

Table 29. Expected Differences in Total Number of Arrests

$v_1 \backslash v_2$	1	2	3	4	5	6	7	8	9	10
1	0	1174	1838	-700	866	219	1613	1941	-759	1506
2		0	664	-1874	-308	-845	438	975	1933	332
3			0	-2538	-971	-1351	-195	311	-2598	-332
4				0	1566	919	2313	2849	-60	2206
5					0	-647	746	1283	-1626	640
6						0	1394	1930	-979	1287
7							0	536	-2373	-106
8								0	-2909	-643
9									0	2266
10										0

Note: This analysis assumes that 2200 female and 15,000 male offenders belong to the offender population. Entries are

$$\text{Arrests } (v_2) - \text{Arrests } (v_1) .$$

rationalistic methods, combining the career criminal cost and recidivism measures used for the male and female offenders and conducting sensitivity analyses on the parameters of the objective function will result in a more informed decision.

First, Table 29 displays the combined savings in crimes committed by men and women over the 35 years planning horizon. Note that if  $v_1 = 1$  is the current policy, the greatest increase in the number of crimes occurs for policy  $v_2 = 8$ , the second highest is  $v_2 = 3$ , and the third and fourth highest policies are  $v_2 = 7$  and  $v_2 = 10$ , respectively. This ranking of the four worst transitions for  $v_1 = 1$ , therefore, has not been disturbed from when the savings in crimes committed was considered only for male offenders. As occurred earlier, the greatest savings in crime appears when the current policy is  $v_1 = 9$  and the policy to be adopted is  $v_2 = 8$ . Identifying dominating policies for the combined male and female recidivism rates, only policy  $v = 8$  dominates all the alternatives, and it dominates because crime increases whenever it is chosen. The dominance of policy 8 is consistent with the results of the male offender analysis; however, for this combined measure, policy 4 does not dominate with respect to the greatest savings in crimes committed. There is not a policy which meets this criteria for the combined crime rates.

Another and, perhaps, more effective way to examine the efficacy of one policy model over another is to combine the career criminal social cost for men and for women into a single statistic.

A weighted performance function is one method that has been selected for this purpose. Define the weighted career criminal social cost as

$$e'_v(\gamma) = F e_{v,f}(\gamma) + M e_{v,m}(\gamma) \quad (6-11)$$

where  $F$  is the percentage of the total offender population that are women,  $M = (1 - F)$  is the percentage that are men,  $e_{v,f}(\gamma)$  is the career criminal social cost for women using policy model  $v$ , and  $e_{v,m}(\gamma)$  is the career criminal social cost for men using policy model  $v$ . The value of  $F$  is determined to be 12.8%, therefore,  $m = 87.2\%$ . As before,  $\gamma$  is the social cost per crime and it is assumed to be equal for men and for women. Because equation 6-10 weights the contribution of each offender category to the objective  $e'_v(\gamma)$  by its representation in the population, another performance criteria might be designed which weights each subpopulation's contribution to the objective equally, regardless of the number of offenders in each category:

$$e''_v(\gamma) = e_{v,f}(\gamma) + e_{v,m}(\gamma) . \quad (6-12)$$

The difference in these two measures is that the minimization of  $e'_v(\gamma)$  places equal importance on each individual offender, whereas  $e''_v(\gamma)$  places equal importance on the subpopulation of men and on the subpopulation of women.

The values of  $e'_v(\gamma)$  and  $e''_v(\gamma)$  are shown in Table 30 for each policy  $v$  and  $\gamma$  assumed equal to \$10,000. Although the rankings are

Table 30. Ranking Policy Alternatives on the Basis of Career Criminal Social Cost for Men and Women

$v$	$e'_v$	Rank ( $e'_v$ )	$e''_v$	Rank ( $e''_v$ )
1	\$66448	10	\$59965	10
2	63966	4	57036	5
3	63649	2	56875	3
4	65170	8	58455	8
5	64033	6	56942	4
6	65291	9	58592	9
7	63984	5	57263	6
8	63889	3	55795	2
9	64773	7	57994	7
10	62494	1	54909	1

not exactly the same for  $e'_v$  and  $e''_v$ , there are tremendous similarities:

1. Policy  $v = 1$  lies at the bottom of each ranking while  $v = 10$  occurs at the top;
2. Policies  $v = 3$  and  $v = 8$  are alternately ranked 2 and 3 on each list, indicating that these policies may be interchangeable for a social optimum with  $\gamma = \$10,000$ ;
3. The positions of policies  $v = 2, 5$  and  $7$  on each list are merely two different permutations of the ranks 4, 5 and 6; thus, these policies may be interchangeable;
4. Policies ranked 7, 8, 9, 10, ( $v = 9, 4, 6$ , and 1, respectively) do not change their positions in the two lists; their desirability is, therefore, fixed at levels undesirable vis-à-vis those policies whose ranks are 1 through 6.

Sensitivity Analysis, Combined Objective. In Section 6.2.3, the value of  $\gamma$  was allowed to vary in order that the appropriate policy model could be selected which minimized the career criminal social cost for any estimate of  $\gamma$ . To repeat this procedure for the weighted objective function is desirable from the point of view that at least the range over which a policy is optimal would change from the case when only male offenders are considered and, perhaps, the optimal policy set itself may change.

To develop an estimate of  $\gamma$  of the form of equation 6-8 for the weighted social cost function, first redefine the weights  $F$  and  $M = (1 - F)$  to be  $F'$  and  $M'$  whose values are unrestricted. Thus,

$$e'''_v(\gamma) = F' e_{v,f}(\gamma) + M' e_{v,m}(\gamma) . \quad (6-13)$$

Equating the weighted social cost functions for two policies  $v$  and  $v_0$ , an estimate of  $\gamma$ , may be found to be

$$\hat{\gamma}'_{v,v_0} = \frac{M'(\bar{C}_{v,m} - \bar{C}_{v_0,m}) + F'(\bar{C}_{v,f} - \bar{C}_{v_0,f})}{M'(\beta_{v_0,m} - \beta_{v,m}) + F'(\beta_{v_0,f} - \beta_{v,f})} \quad (6-14)$$

where  $\bar{C}_{r,m}$  is the career criminal cost of policy  $r$  for male offenders,  $\bar{C}_{r,f}$  is the career criminal cost of policy  $r$  for female offenders,  $\beta_{r,m}$  is the recidivism rate of policy  $r$  for male career criminals,  $\beta_{r,f}$  is the recidivism rate of policy  $r$  for female career criminals,  $M'$  is the weight given to the male subpopulation, and  $F'$  is the weight given to the female subpopulation.

Determining the range of  $\gamma$  over which a policy is optimal, two

cases are evaluated:  $F'_1 = 12.8\%$ ,  $M'_1 = 87.2\%$  and  $F'_2 = M'_2 = 1$ .

For both cases, policy 10 is optimal over a range of  $\gamma$  and policy 9 is optimal over the remainder of the range of  $\gamma$ . (See Table 31.)

Table 31. Determining  $\hat{\gamma}'_{v,v_0}$  for the Combined Career Criminal Social Cost for Men and Women

$v_0 \backslash v$				
$v \backslash v_0$	10	9	10	9
1	55,144	-27,916	70,551	-49,712
2	86,139	17,181	83,362	20,949
3	-49,876	17,444	-221,294	18,956
4	30,857	-103,486	119,645	-17,939
5	51,381	17,803	73,547	22,450
6	47,336	891	61,518	-3,289
7	-230,630	15,726	1,187,000	16,389
8	-27,310	15,218	-32,214	25,993
9	27,285	—	36,485	—
10	—	—	—	—
$M' = .872, F' = .128$			$F' = M' = 1.0$	

This contradicts the results for male offenders alone where policy 4 also became optimal for  $\gamma \geq \$385,000$ . The fact that policies 10 and 9 are both optimal is re-assuring in that the choice of the optimal policy set is indifferent to the weights  $F'$  and  $M'$ ; this is not to say, however, that the choice of the optimal policy is indifferent to the values of  $F'$  and  $M'$  or to the value of  $\gamma$ .



### 6.3 Summary

It was the purpose of this chapter to describe and analyze experiments conducted on the simulation model to evaluate the effect of plea bargaining scenarios on the efficacy of a representative CJS. Several performance measures have been discussed in this chapter:

1. Total CJS cost over the planning horizon,
2. Average number of offenses per criminal career,
3. Average career criminal cost,
4. Total index crimes prevented over the planning horizon,
5. Average career criminal social cost.

The last measure, the career criminal social cost, was chosen as the global performance criteria because of the strong negative relationship which exists between CJS cost and the rate of recidivism.

Using the career criminal social cost to evaluate the alternatives, having the prosecutor respond to an offender's criminal record results in the minimum social cost per offender career. However, the value of the social cost per offense  $\gamma$  and the weight given to each offender category (males versus females) determines how the prosecutor should respond and it also determines whether or not increasing the prosecutor's budget will improve the career criminal social cost. If no weight is given to the female subpopulation, the prosecutor should send to trial the first offenders if  $\gamma > \$24,606$ . If  $\gamma \leq \$24,606$ , however, he should send those offenders who are known to be repeaters to trial. In addition, if  $\gamma \leq \$385,000$  increasing the prosecutor's budget by 10% in order to prosecute more offenders reduces the career criminal

social cost.

If, on the other hand, the weight given to women for reducing their career criminal social cost is in proportion to the percentage representation in the criminal population or if it is the same for both offender categories, then different policy sets result. For either weight distribution, the optimal policy structure requires that the prosecutor's budget be increased by 10% and that the arrest record be used to dispose of each defendant at the plea bargaining decision point. However, the value of  $\gamma$  again dictates how the prosecutor is to dispose of defendants. For either weight distribution, when  $\gamma$  is low the prosecutor should send to trial those offenders who have been arrested at least once before. When  $\gamma$  is large, the prosecutor should allow the repeat offender to negotiate a guilty plea and send to trial the first-offender. The threshold of  $\gamma$  at which this policy change occurs varies depending on the weight distribution. If the women are weighted in proportion to their representation in the offender population, then the threshold value of  $\gamma$  occurs at \$27,285; if women are weighted the same amount as are men, this threshold occurs at \$36,485.

## CHAPTER VII

### CONCLUSIONS

#### 7.1 Summary of Results

The purpose of this research was to develop a discrete event simulation model of the Criminal Justice System that represents the state-of-the-art in modeling technology. In Chapter II, the existing models of the CJS were surveyed in order to ascertain both the strengths and the weaknesses of these earlier works, and a summary of the attributes of several important works were tabulated. From this compilation of model characteristics, it was observed that not one of these earlier models possesses a majority of the attributes that are listed. The simulation model developed for this research, however, possesses many of these characteristics. Because the resulting model is a simulation as opposed to an analytical work, it is not restricted by the inability to solve the more complex mathematical formulations. This flexibility in modeling large-scale systems is not purchased without a cost; however, the more general the model the greater are the difficulties in collecting data, in analyzing the model's output, and increasing a user's appreciation of the model's validity and internal consistency.

In Chapter III, a resource-constrained economic model of plea bargaining was examined. After determining that such a model is adaptable to a simulation, the effect on plea bargained outcomes

was postulated when different types of case-specific information are available to the prosecutor. The expected response to such information was formulated under the assumption that specific policy directives had not been given the prosecutor concerning how the information should be used to dispose of offenders.

The structure of the simulation model has been described in Chapter IV. The GNS model developed consists of the following major CJS components: police, prosecution and court, corrections and juvenile justice subsystems. Some of the model's capabilities follow.

1. The model has the ability to trace the criminal careers of offenders.
2. Queueing, resource constraint and costing elements help to describe CJS operations.
3. A recidivism model determines the probability and delay until re-arrest as a function of an offender's sex, and of his last offense and CJS disposition.
4. The interactions of CJS subsystems and the effects that policy changes have on resource requirements and on system performance measures can be explored.
5. A sufficiently detailed CJS structure allows the examination of a variety of scenarios dealing with such aspects of CJS policy as deterrence, deterministic sentences, the elimination of parole, alternative pre-trial release programs, and juvenile justice policy in addition

to plea bargaining alternatives.

The model's output consists of the following statistics:

1. Resource usage statistics
2. CJS cost estimates
3. Queueing statistics
4. Career criminal statistics
5. Crime and recidivism estimates

In Chapter V, this model was implemented with data collected from representative agencies. In addition, it was demonstrated that a heuristic procedure can be used successfully to determine the model's run length. The output from sample runs was also validated by several tests which concentrated on component, input-output transfer function, and internal consistency issues. One test which the model failed to pass was its understatement of the average number of offenses per criminal career. This inadequacy was explained as being due in part to the exponential assumption of the length of the remaining lifetime of offenders. However, the formulation of another model of the life of a criminal was left as a topic for future investigation.

In initializing the model, it was determined that a 2.5% annual growth rate can be used to constrain the court and prosecution resource usage without seriously affecting the queueing behavior of the system over the next 35 years. This result subsumes that the first offender arrest rates are formulated as non-stationary models whose parameters correspond to Deutsch's estimates [24] for Los Angeles County.

In Chapter VI, several policy scenarios were examined using two measures of the social cost of crime, the total and the career criminal social costs, in order to demonstrate how such a model might be used to analyze policy alternatives. The social cost measures were chosen because of the strong negative correlation between recidivism on the one hand and CJS cost on the other. Thus, by combining both of these more common performance measures into a measure of the social cost to society (either total or per criminal career), a much simpler one-dimensional optimization problem is derived. To complement this optimization process, a method of examining the sensitivity of the policy decision to the single parameter of the social cost model was demonstrated. This required determining the intersection points for the constraints of the convex set defined by the social cost models for each policy. Having these intersection points, then, defines the range of the parameter over which a particular policy is optimal.

Another issue addressed in Chapter VI deals with the characteristics of the offender population. Several performance measures were reported for male and female offenders. It was shown that the career criminal cost and recidivism for men is higher than for women. However, more important than the summarization of performance measures for offender categories, the optimization of social costs showed how applying different importance weights to the offender categories can produce different optimal policy sets, where an optimal policy set is defined as the collection of policy alternatives which are

optimal for a given weight vector over some range of the social cost parameter. Since several policies were also shown to have a different impact on each offender category, several weighting functions were examined.

Regardless of the weight vectors assumed, the minimum career criminal social cost was obtained when the prosecutor responds to the number of previous arrests of each offender. However, the importance weight for each sex dictated the range of the social cost per crime over which each policy was optimal and whether or not an increase in the prosecutor's budget was necessary to reduce the career criminal social cost of a policy. The results for each weight vector used showed that, if the social cost per crime was low, the prosecutor should try to send to trial all offenders who have been arrested at least once before. If, on the other hand, the social cost per crime is high, the prosecutor should allow recidivists to plead guilty while sending first offenders to trial whenever possible.

## 7.2 Recommendations for Further Research

The simulation model which is a product of this research can be used to address a wide range of CJS policy areas. However, before any further substantive experimental efforts are made, additional work on the model itself is suggested. In particular, the following areas might be considered:

1. The cost model can be expanded to include annual fixed costs for the various processors;

2. The resource model might be expanded to include additional resource types so that a correspondence exists between a server in the model and an actual server;
3. The model of the lifetime of an offender should be re-formulated in order for the number of arrests per offender to compare more favorably with those developed by the FBI [29];
4. A model of deterrence is missing from the current simulation while any investigation of actual policy alternatives should incorporate such aspects into the experimental design;
5. Further enhancement of the plea bargaining decision functions should be based upon a better studied model than the multiplication functions developed in Chapter VI, although the plea bargaining structure itself should not need revision.

In addition to the above recommendations, because the time to execute this model is approximately two CPU hours on a CDC Cyber 74, ways to reduce the execution time should be considered. Two workable suggestions are that some of the detail in the model be aggregated in those subsystems in which a particular study does not require this level of abstraction. Another potential remedy for the cost of executing this model is to use a scaling factor for the virgin arrest rates. Further effort should be directed toward determining the relationships in performance levels of the scaled version and the



full size system. However, it was noted in Chapter V that scaling down the forecasts did not produce any observable change in the shape of the time histories produced by the model. Since scaling the input stream to reduce the execution time requirements also shortens the length of the queueing lists, forecast scaling would be an excellent way to decrease computer execution costs and storage needs for this model.

## APPENDIX A

## INPUT DESCRIPTION

## APPENDIX A

### INPUT DESCRIPTION

Three types of inputs are required for this GNS model of the Criminal Justice System:

1. GNS - required data
2. CJS - specific data
3. A virgin arrestee forecasting function

#### GNS Inputs

The first category is the data required to implement the model using GNS. That is, data specifying the model's structure, the GNS facilities to be used, and the statistics to be collected for the model's output all belong to this first category. Thus, this data prepares the Generalized Network Simulator for the special structure of the CJS model and the subroutines, which facilitate this structure, given in Appendix D. Since these parameters do not change throughout the experimentation, the actual data used is displayed in Appendix B while the definitions of the variables may be found in the GNS Reference Manual [36].

#### CJS Inputs

The second type of input required is specific to this model of the CJS, and it is fed to the model using the FORTRAN macro namelist. There are ten namelist variables in use. Following is a description of each namelist (in the order that each must appear

in the input file). Sample data is shown in Appendix B.

#### PARAM Namelist

This namelist possesses the basic parameters of the model of the Criminal Justice System.

- ADULT      is the age at which an offender is considered to be an adult.
- DUMP      is a logical variable. If it is true, the input data is echoed before the simulation begins.
- ICCC      is the divisor which reduces the career criminal cost statistic to facilitate the printing of a histogram (see also MICCC).
- MBEGIN    is the number of the month in which the prosecutor's budget is changed, and it is also the month in which a management information system (see MIS) becomes available for tracking recidivists.
- MEHIS     is a plea bargaining parameter. It is set to 1 if each offender's criminal history affects the prosecutor's first decision, 2 if it affects the second decision, 3 if it affects both decisions, and 0 otherwise.
- MEQUE     is a plea bargaining parameter. If the current size of the pre-trial queue relative to a base value (see SINITQ) affects the prosecutor's first decision, then MEQUE = 1; if only the second decision, MEQUE = 2; both decisions, MEQUE = 3. Otherwise, MEQUE = 0.
- MERES     is a plea bargaining parameter which is 1 if the prosecutor's first decision is affected by increases in his

budget, 2 if his second decision is affected, 3 if both are affected, or 0 if neither. (See also PRG.)

MESEV is a plea bargaining parameter which is 1 if the severity of each offender's latest offense affects the prosecutor's first decision, 2 for the second decision, 3 for both, or 0 for neither.

MICCC is the number of bars reserved for the histogram of career cost.

MIS is the cost per offender per day of maintaining a management information system which is used to track recidivists.

NCHARG is the number of final charges available for convicting a defendant in the superior court.

NCRIME is the number of crime categories (initial charges) examined.

NDISP is the number of correctional dispositions available to the superior and criminal courts. NDISP does not necessarily mean the number of separate facilities, since for example each sex may be assigned to a different facility for the same disposition (e.g., prison).

NEBOX is the number of times namelist FLOUT is input.

NOC is the number of demographic categories of offenders being simulated.

NSBOX is the number of times namelist STIME is input.

NSDISP is the number of correctional dispositions available to the superior and criminal courts which require a period of supervision by the CJS.

PRG is the percentage increase in the prosecutor's budget that

occurs at time MBEGIN if MERES>0. (It is expressed as a decimal fraction.)

RGROW is a vector whose elements are the growth rates for each of the CJS resources. (Expressed as decimal fractions.)

RTIME is the number of years following TINITL during which CJS resource statistics are collected.

SINITQ is the baseline value of the superior court's pre-trial queue (Boxes 37,39) length which is used to affect the prosecutor's plea bargaining decisions.

TRACEF is a logical variable that, when true, causes the forecasts of the virgin arrest rates for each crime to be printed for each simulated month.

TSTOP is the number of years (run length) to be simulated during the experimental epoch.

TINITL is the number of years required to initialize the model.

#### OFFENDER Namelist

This namelist is repeated NOC times, once for each demographic category being simulated. The purpose of each repetition is to describe the characteristics of each offender category. The number of demographic categories must always be a multiple of two. The odd numbered categories must describe male offenders; the even numbered categories must describe female offenders. The following are vectors whose elements correspond to each of the NCRIME offenses:

ABAR is the average age of first arrest for the offenders in each category.

AMAX is the maximum recorded age at which an offender is

arrested.

AMIN is the minimum recorded age at which a first-offender is arrested.

ASD is the standard deviation of the first arrest age for each of the NCRIME offenses.

CAT is the offender category number.  $CAT = 1, 2, \dots, NOC$ .

PPOP represents the percentage (decimal) of the virgin arrest population that commits each of the NCRIME offenses and that is also a member of the associated offender category. Hence, summing PPOP over all NOC offender categories for any single offense yields one.

#### STIME Namelist

This namelist is also repeated several times (see NSBOX). Its purpose is to describe the service times which vary by crime type for each queue box in the network. Each box must also be listed as a start control box in the GNS network description. (That is,  $STARTC = TRUE$ .)

ID is the queue box number as represented in the network diagram and as identified in the BOX namelist of the GNS input data.

TBAR is a vector of service times for the queue box identified as ID. Each element in TBAR is the average number of days required to service an offender who commits one of the NCRIME offense types. Exponential service distributions are always assumed.

FLOUT Namelist

The namelist FLOUT is used to input crime-specific branching ratios for NEBOX of the end control boxes in the GNS input data (ENDC = TRUE).

ARC is an array of branching probabilities. For each arc identified in IDARCS, branching probabilities must be input for each of the NCRIME offense types. For simplicity, each row of this matrix should be reserved for only one arc, and it should contain NCRIME elements.

ID is the number of the box whose output arcs are described by this namelist.

IDARCS is the number of the successor boxes to which these output arcs are directed. Each value must correspond in the precise order to those boxes listed as successors of ID in the GNS input data (That is, IDARCS(i) = IFOLL(i) for  $i = 1, \dots, \text{NARC}$ ).

NARC is the number of arcs emanating from box ID.

CRIMES Namelist

This namelist consists of several arrays which describe crime-specific information.

AJAIL is the probability that an adult arrestee is detained (jailed) by the CJS before trial. There exist NCRIME elements for this vector.

ANO is the average number of arrests in an offender's career, given that his latest offense is one of the NCRIME offense types.



CJAIL is the probability that an adult offender, who is detained by the CJS before his trial, is still under its custody at the time of his trial. NCRIME probabilities are input.

SEVERE is a vector which contains measures of the relative severity of each of the NCRIME offense categories.

SWITCH is the crime-switch matrix. It is an NCRIME-by-NCRIME array of probabilities which predicts, based on the latest crime for which the offender is arrested, the crime type if the offender is arrested again. The rows of the matrix represent the offense and the columns the subsequent or predicted offense.

YJAIL is an NCRIME-element vector of the probabilities that a juvenile offender will be detained by the CJS beginning with the juvenile intake hearing and ending at the completion of the juvenile court's hearing.

#### PLEA Namelist

This namelist consists of three matrices which deal with plea bargaining.

BARGAN is an array of probabilities which predicts the conviction charge based upon the offense category under which the offender was last arrested. Each of the NCHARG rows of the matrix represents one of the conviction labels, while each column represents one of the NCRIME crime categories.

PDISP is an array of sentencing probabilities. Each row of this matrix represents one of the NDISP sentencing dispositions of the courts. Each row must contain 15 elements, the first NCHARG of which are the probabilities that offenders

whose conviction labels are given are sentenced to the respective disposition. The last (15-NCHARG) elements of each row must be zeroes.

PSDUR is an array of sentence lengths for the NSDISP dispositions which require CJS monitoring of an offender. Each row of this matrix represents one of these dispositions, and it must contain 15 elements. The first NCHARG elements of a row are the sentence durations (in days) corresponding to the conviction charges. The remaining elements of each row must be zeroes.

#### COURT Namelist

The COURT namelist consists of three matrices that predict the conviction and sentencing states of offenders whose cases are tried before a justice of the superior court.

CONVIC is a matrix of conviction probabilities which is constructed exactly like BARGAN from the PLEA namelist.

TDISP is an NDISP-by-15 matrix composed of sentencing probabilities for the NDISP dispositions. This matrix is constructed like PDISP from namelist PLEA.

TSDUR is an matrix of sentence lengths (in days) of those dispositions which require CJS monitoring. This matrix is input exactly like PSDUR.

#### LCOURT Namelist

This namelist consists of two matrices which describe the sentencing states of the lower (criminal) court.

DISPL is composed of the sentence probabilities for the NDISP

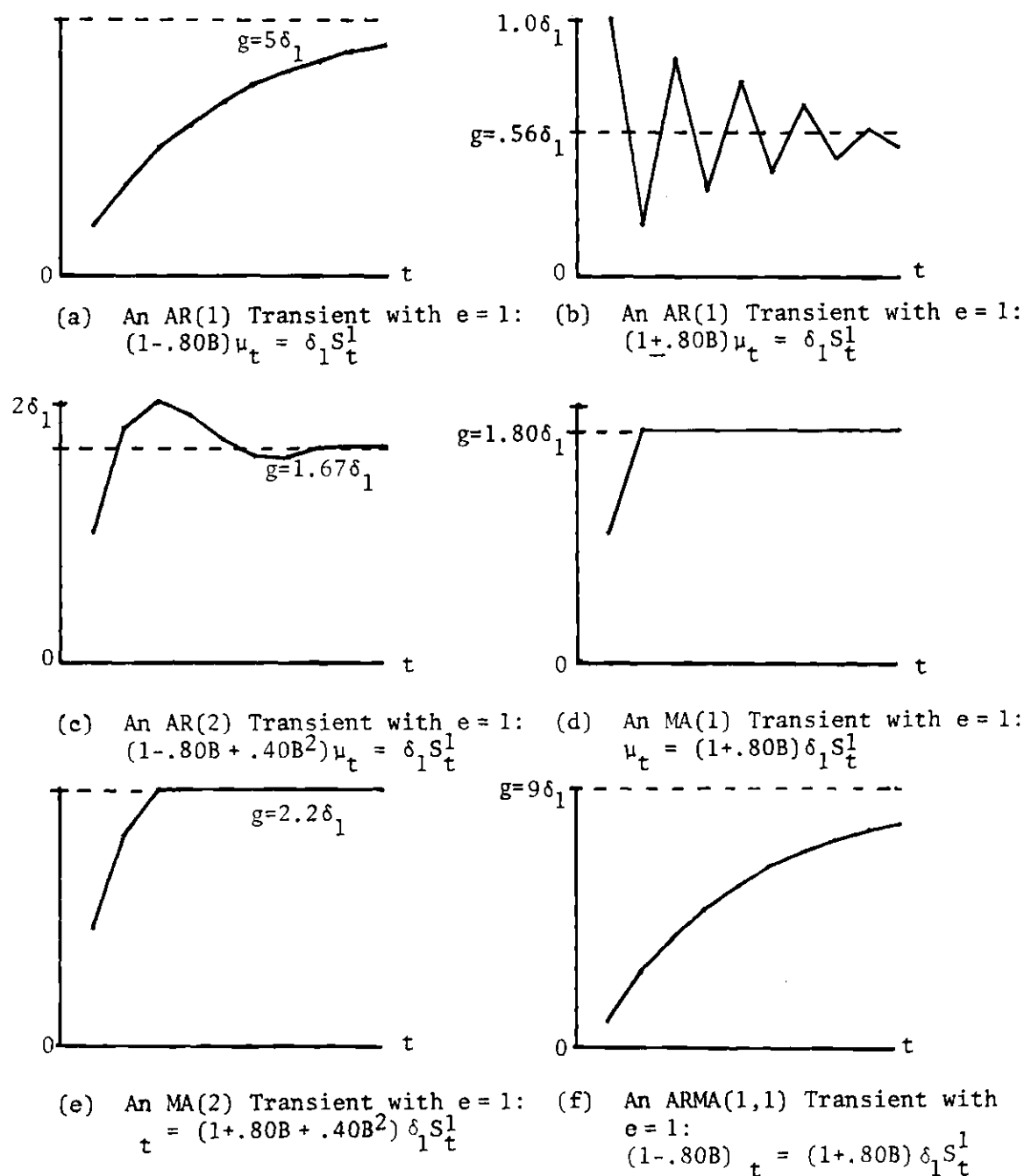


Figure 12. Examples of Transient Mean Functions for Stationary Initially Relaxed Time Series Models with  $e = 1$

dispositions. Since conviction labels are ignored in the lower court, this matrix is structured exactly like TDISP with the exception that the seven columns represent the crime labels instead of the conviction labels. If NCRIME is less than seven, then the final (7-NCRIME) columns are all zero-filled.

SDURL is the sentence duration in days for each NSDISP disposition which requires CJS monitoring. Each row represents one of these dispositions and the first NCRIME elements of the row are composed of sentence lengths for the crime categories. All other elements of the matrix are zero.

#### PAROLE Namelist

With the issue of prisoner parole currently under scrutiny, the parole model must be well developed. This namelist inputs the necessary charge-specific parole data.

DPAROL is a vector, the first NCHARG elements of which are the average number of days that an offender convicted of one of the final conviction labels is on parole. The remaining (15-NCHARG) elements are zero.

PRISONF is a vector representing the percentage of the prison sentence that female offenders actually serve before their release on parole. The last (15-NCHARG) elements of the vector are zero.

PRISONM is a vector representing the percentage of the sentence that a male prisoner actually serves before his release on parole. The final (15-NCHARG) elements of the vector

are zero.

PVIOL is a vector representing the probability of a parole violation which results in the offender's return to prison. The final (15-NCHARG) elements are zero.

#### RECID Namelist

This namelist serves to input the probabilities of recidivism and the delays between an offender's release from the CJS and his subsequent re-arrest. The re-arrest probabilities are based upon the age and sex of the offender, while the delays are based upon his age and upon the type of CJS disposition. The actual age of an offender, AGE, is grouped according to the following algorithm:

```

IAGE = AGE/5. -2
IF (IAGE. LE.0) IAGE = 1
IF (IAGE. GE.7) IAGE = IAGE-1
IF (IAGE. GE.8) IAGE = 7

```

Thus, only seven age categories are considered. Each of the following input variables are vectors; each element in a vector corresponds to a particular age category.

DELDIS is the delay (in days) until re-arrest of those offenders whose cases are dismissed or who are themselves acquitted of all charges.

DELFI is the delay (in days) until re-arrest of those offenders who are fined.

DELPAR is the delay (in days) until an offender who successfully completes parole is re-arrested.

DELPRI is the delay (in days) until the re-arrest of an offender who is released from prison.

DELPRO is the delay (in days) until the re-arrest of an offender who is either sentenced to a probationary period or who receives a suspended sentence.

PROBF is the probability that a woman will be re-arrested.

PROBM is the probability that a man will be re-arrested.

#### Forecasting Function

The third and final input for this GNS model of the Criminal Justice System is a forecasting function which predicts the number of virgin arrests for each simulated month and crime. The following requirements exist for this function:

1. The name of the function must be FORCAST
2. The input parameters are
  - a. The forecast month
$$\text{MONTH} = 1, 2, 3, \dots, 12(\text{TSTOP} - \text{TINITL} + 1)$$
  - b. The crime category
$$\text{ICRIME} = 1, 2, 3, \dots, \text{NCRIME}$$
3. The output of the function is the number of persons arrested during MONTH for ICRIME who have never before been arrested.

## APPENDIX B

## SAMPLE INPUT

GNS Data

```

$RUN IDRUN=1, MENTRY=6440, NATRIB=5, MBOX=57, NBOX=49,
NETRL=9.E5, NOPREM=.TRUE.,
NTRACE=0, KARD=0, NODIAG=.TRUE., NODMP=.TRUE., NSINK=8, NSOUR=1,
RESC=.TRUE., MRES=10, MMRES=10,
QUE=.TRUE., NQBOX=24, IPRTY=2,
COST=.TRUE., IRATE=0, ISTUP=0, NGRP=7,
UTIME=0., UIN=.TRUE., UOUT=.TRUE., USTC=.TRUE., UENC=.TRUE.,
$END

$RESIN MAXL= 24,99999, 3,99999,99999,99999,99999,99999,99999,99999,
KOST= 425, 4010, 1550, 336, 474, 103, 20, 10, 145, 544,
$END

$BOX ID=1, ENDC=.TRUE., NFRL=0, NPRL=1, DUR=30., IFOLL=1, $END
$BOX ID=2, ENDC=.TRUE., NPRL=1, IFOLL=4,5, DUR=0., $END
$BOX ID=3, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=4, STARTC=.TRUE., NPRL=1, IFOLL=28, DUR=0., $END
$BOX ID=5, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,1, STARTC=.TRUE.,
ENDC=.TRUE., DUR=0., IFOLL=8,21, JGRP=1, $END
$BOX ID=7, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=8, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,1,0,
IFOLL=9,23,52, STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=2, $END
$BOX ID=9, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, IFOLL=12,13,14,15,23,52,
LR=0,0,0,1, STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=2, $END
$BOX ID=10, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,0,1,
ITYPE=12, JGRP=7, $END
$BOX ID=12, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,1,0,0,0,
STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=3, IFOLL=53, $END
$BOX ID=13, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,1,0,0,0,
STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=3, IFOLL=53, $END
$BOX ID=14, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,1,0,0,0,
STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=3, IFOLL=53, $END
$BOX ID=15, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,1,0,0,0,
STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=3, IFOLL=53, $END
$BOX ID=18, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=19, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, IFOLL=20, STARTC=.TRUE.,
DUR=0., $END
$BOX ID=20, STARTC=.TRUE., ENDC=.TRUE., NPRL=1, IFOLL=4,5, DUR=0., $END
$BOX ID=21, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,1,0, IFOLL=23,
STARTC=.TRUE., DUR=0., JGRP=4, $END
$BOX ID=22, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,0,0,1,
ITYPE=12, JGRP=7, $END
$BOX ID=23, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=1,0,0,0,0,0,0,0,0,0,
STARTC=.TRUE., ENDC=.TRUE., IFOLL=25,28,54, DUR=0., JGRP=4, $END
$BOX ID=25, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,1,0,0,0,0,0,1,
STARTC=.TRUE., ENDC=.TRUE., DUR=0., IFOLL=26,40,41,42,43,44,50,51,
JGRP=5, $END
$BOX ID=26, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,1,0,0,
IFOLL=57, STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=6, $END

```



```

$BOX ID=27, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=28, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=1,0,0,0,1,0,0,0,0,0,
  IFOLL=29,30, STARTC=.TRUE., ENDC=.TRUE., DUR=0., JGRP=4, $END
$BOX ID=29, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=54, $END
$BOX ID=30, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=31,32, $END
$BOX ID=31, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=54, $END
$BOX ID=32, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=37,39, $END
$BOX ID=34, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=35, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=36, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=37, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=1,0,1,0,0,0,0,0,0,0,
  ENDC=.TRUE., IYPE=6, PARAM=2,1, IFOLL=26,40,41,42,43,44,50,51,
  JGRP=5, $END
$BOX ID=39, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=1,0,1,0,0,0,0,0,0,1,
  STARTC=.TRUE., ENDC=.TRUE., DUR=0., IFOLL=26,40,41,42,43,44,50,51,
  JGRP=5, $END
$BOX ID=40, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,0,1,0,0,
  JGRP=6, ENDC=.TRUE., STARTC=.TRUE., DUR=0., IFOLL=45,56, $END
$BOX ID=41, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,0,1,0,0,
  JGRP=6, ENDC=.TRUE., STARTC=.TRUE., DUR=0., IFOLL=45,56, $END
$BOX ID=42, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,0,1,0,
  JGRP=6, STARTC=.TRUE., ENDC=.TRUE., DUR=0., IFOLL=56, $END
$BOX ID=43, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=57, $END
$BOX ID=44, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=57, $END
$BOX ID=45, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,0,1,0,
  JGRP=6, STARTC=.TRUE., ENDC=.TRUE., DUR=0., IFOLL=40,41,56, $END
$BOX ID=46, SINK=.TRUE., STARTC=.TRUE., NPRL=1, DUR=0., $END
$BOX ID=47, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, IFOLL=49, STARTC=.TRUE.,
  DUR=0., $END
$BOX ID=48, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, IFOLL=49, STARTC=.TRUE.,
  DUR=0., $END
$BOX ID=49, STARTC=.TRUE., ENDC=.TRUE., NPRL=1, IFOLL=4,5, DUR=0., $END
$BOX ID=50, ENDC=.TRUE., NPRL=1, DUR=0., IFOLL=57, $END
$BOX ID=51, QBOX=.TRUE., NPRL=9.E5, NSERV=9.E5, LR=0,0,0,0,0,0,0,1,0,0,
  JGRP=6, STARTC=.TRUE., ENDC=.TRUE., DUR=0., IFOLL=57, $END
$BOX ID=52, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=7,19, $END
$BOX ID=53, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=18,19, $END
$BOX ID=54, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=27,48, $END
$BOX ID=56, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=36,46,47, $END
$BOX ID=57, ENDC=.TRUE., DUR=0., NPRL=1, IFOLL=34,35,48, $END

```

\$STAT

```

IN= p6,
    8,19,22,
    23,25,26,28,37,39,
    48,42,45,47,48,
HISTI=0.,
HISTL=0.,
NCELL=0,
FSHOT=360,
TCALL=360,
NCELL=55,
$END

```

## CJS Data

```

$PARAM NCRIME=7, NCHARG=9, NDISP=6, NSDISP=3, DUMP=.FALSE., NOC=2,
  ADULT=18., NSBOX=12, NEBOX=9, TRACEF=.FALSE., SINITQ=10.,
  MBEGIN=246, MEQUE=3, MERES=3, MESEV=3, MENIS=0, MIS=0, PRG=0.10,
  RTIME=55., TSTOP=55.18, TINITL=20.88, ICC=1580, NICC=58,
  RGROW=.025,0.,.025,0.,0.,0.,0.,0.,0.,0.,
$SEND
$OFFENDR CAT=1.,
  PPOP=.875, .953, .905, .897, .815, .946, .998,
  ABAR=32.9, 25.9, 30.4, 26.2, 31.3, 24.8, 27.2,
  ASD= 13.0, 8.4, 11.9, 9.3, 11.5, 8.6, 9.2,
  AMIN= 16., 16., 11., 11., 16., 16., 16.,
  AMAX= 70., 65., 75., 75., 78., 70., 65.,
$SEND
$OFFENDR CAT=2.,
  PPOP=.125, .847, .095, .103, .185, .054, .010,
  ABAR=35.0, 25.8, 33.6, 27.8, 31.2, 24.4, 22.5,
  ASD= 9.2, 7.6, 12.1, 9.7, 10.2, 7.7, .5,
  AMIN= 21., 16., 16., 16., 16., 16., 21.,
  AMAX= 55., 58., 65., 65., 65., 55., 25.,
$SEND
$STIME ID= 5, TBAR=7*1.0, $SEND
$STIME ID= 8, TBAR=7*38., $SEND
$STIME ID= 9, TBAR=7*38., $SEND
$STIME ID=12, TBAR=1680., 1488., 1362., 1415., 1392., 1460., 1620., $SEND
$STIME ID=13, TBAR= 885., 800., 718., 748., 737., 770., 848., $SEND
$STIME ID=14, TBAR= 885., 800., 718., 748., 737., 770., 848., $SEND
$STIME ID=15, TBAR= 90., 111.1, 73.6, 81.7, 82.8, 79., 75.1, $SEND
$STIME ID=21, TBAR=7*1.0, $SEND
$STIME ID=23, TBAR= 8.5, 6.8, 10.8, 8.7, 12.6, 6.0, 10.8, $SEND
$STIME ID=25, TBAR= 26.8, 7.1, 7.3, 6.3, 4.7, 11.2, 9.8, $SEND
$STIME ID=28, TBAR=7*7.8, $SEND
$STIME ID=39, TBAR= 30.4, 17.7, 11.1, 9.7, 9.1, 9.9, 13.5, $SEND
$FLOUT ID=2, NARC=2, IDARCS=4, 5,
  ARC=.050, .094, .127, .189, .275, .162, .087,
  .958, .906, .873, .811, .725, .838, .913,
$SEND
$FLOUT ID=8, NARC=3, IDARCS=9, 23, 52,
  ARC=.683, .479, .603, .479, .479, .479, .603,
  .8., .8., .8., .8., .8., .8., .8.,
  .397, .521, .397, .521, .521, .521, .397,
$SEND
$FLOUT ID=9, NARC=6, IDARCS=12, 13, 14, 15, 23, 52,
  ARC=.125, .057, .125, .057, .057, .057, .125,
  .390, .431, .390, .431, .431, .431, .390,
  .408, .277, .408, .277, .277, .277, .408,
  .085, .235, .085, .235, .235, .235, .085,
  .8., .8., .8., .8., .8., .8., .8.,
  .8., .8., .8., .8., .8., .8., .8.,
$SEND

```

```

$FLOUT ID=20, NARC=2, IDARCS=4, 5,
  ARC=.050, .094, .127, .189, .275, .162, .007,
    .950, .906, .073, .011, .725, .030, .913,
  $END
$FLOUT ID=23, NARC=3, IDARCS=25, 20, 54,
  ARC=.112, .042, .250, .171, .237, .095, .111,
    .624, .607, .344, .515, .399, .434, .477,
    .265, .351, .406, .314, .364, .471, .412,
  $END
$FLOUT ID=28, NARC=2, IDARCS=29, 30,
  ARC= 0., 0., 0., 0., 0., 0., 0.,
    1., 1., 1., 1., 1., 1., 1.,
  $END
$FLOUT ID=30, NARC=2, IDARCS=31, 32,
  ARC= 0., 0., 0., 0., 0., 0., 0.,
    1., 1., 1., 1., 1., 1., 1.,
  $END
$FLOUT ID=32, NARC=2, IDARCS=37, 39,
  ARC=.608, .726, .697, .000, .035, .026, .700,
    .392, .274, .303, .120, .165, .174, .300,
  $END
$FLOUT ID=49, NARC=2, IDARCS=4, 5,
  ARC=.050, .094, .127, .189, .275, .162, .007,
    .950, .906, .073, .011, .725, .030, .913,
  $END
$CRIMES
  SWITCH=.025, .025, .150, .400, .200, .100, .100,
    .015, .010, .350, .060, .350, .115, .100,
    .025, .040, .150, .300, .005, .200, .200,
    .010, .020, .135, .063, .459, .202, .031,
    .010, .020, .140, .025, .400, .275, .130,
    .010, .027, .045, .020, .390, .222, .270,
    .020, .150, .110, .260, .200, .140, .120,
  SEVERE=33.3, 6.43, 9.74, 2.64, 2.26, 2.29, 15.3,
  YJAIL= .523, .209, .216, .136, .136, .136, .364,
  AJAIL= .523, .209, .216, .136, .136, .136, .364,
  CJAIL= .430, .430, .430, .430, .430, .430, .430,
  AND= 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
  $END
$PLEA
  BARGAN=.400, 0., .003, 0., 0., 0., 0.,
    .091, 0., 0., 0., 0., 0., 0.,
    .354, 0., .003, 0., 0., 0., 0.,
    .020, .703, .017, .010, 0., .007, .020,
    .127, .029, .949, .020, .010, 0., .143,
    0., .003, .011, .050, .029, .014, .041,
    0., .163, .011, .090, .913, .055, 0.,
    0., .003, .006, .012, .040, .924, 0.,
    0., .019, 0., .002, 0., 0., .796,
  30*0.,
  PDISP=.910, .700, .490, .094, .450, .590, .396, .600, .450,
  6*0.,

```

```

      .898, .388, .518, .106, .498, .400, .584, .316, .523,
6*0.,
      0., 0., 0., 0., 0., 0., 0., 0., 0.,
6*0.,
      0., 0., 0., 0., .850, .818, .816, .884, .819,
6*0.,
      0., 0., 0., 0., .810, 0., .884, 0., 0.,
6*0.,
      0., 0., 0., 0., 0., 0., 0., 0., 0.,
6*0.,
PSDUR=6430., 4493., 2892., 2941., 1346., 1955., 1458., 1544., 3611.,
6*0.,
1680., 1680., 1680., 1488., 1362., 1415., 1392., 1460., 1620.,
6*0.,
      0., 0., 0., 0., 0., 0., 0., 0., 0.,
6*0.,

$END
$COURT
CONVIC=.408, 0., .883, 0., 0., 0., 0.,
      .891, 0., 0., 0., 0., 0., 0.,
      .354, 0., .883, 0., 0., 0., 0.,
      .028, .783, .817, .818, 0., .887, .820,
      .127, .829, .949, .828, .818, 0., .143,
      0., .803, .811, .858, .829, .814, .841,
      0., .163, .811, .898, .913, .855, 0.,
      0., .803, .886, .812, .848, .924, 0.,
      0., .819, 0., .802, 0., 0., .796,
38*0.,
TDISP=.855, .656, .454, .867, .423, .581, .383, .660, .417,
6*0.,
      .885, .281, .472, .103, .460, .394, .565, .307, .477,
6*0.,
      .868, .863, .874, .838, .861, .816, .832, .829, .889,
6*0.,
      0., 0., 0., 0., .847, .818, .816, .884, .817,
6*0.,
      0., 0., 0., 0., .889, 0., .884, 0., 0.,
6*0.,
15*0.,
TSDUR=11437., 8467., 3945., 5540., 2538., 3686., 2750., 2912., 6804.,
6*0.,
1680., 1680., 1680., 1488., 1362., 1415., 1392., 1460., 1620.,
6*0.,
      0., 0., 0., 0., 0., 0., 0., 0., 0.,
6*0.,

$END
$LCOURT
DISPL= 0., 0., 0., 0., 0., 0., 0.,
      .889, .158, .447, .451, .407, .388, .660,
      0., 0., 0., 0., 0., 0., 0.,
      .837, .853, .879, .844, .861, .823, 0.,
      0., .818, .882, .820, 0., .818, .820,
      .874, .772, .472, .485, .533, .579, .328,

```

SDURL= 0., 0., 8., 0., 8., 6., 0.,  
 1388., 1239., 1344., 1374., 1377., 1380., 1428.,  
 90., 111.1, 73.6, 81.7, 82.8, 79.0, 75.1,

SEND

\$PAROLE

PRISONM= .359, .514, .381, .369, .444, .320, .312, .332, .663, 6\*0.,  
 PRISONF= .195, .279, .273, .224, .233, .219, .274, .184, .197, 6\*0.,  
 PVIOL= .220, .220, .220, .220, .220, .220, .220, .220, .220, 6\*0.,  
 DPAROL=9\*738., 6\*0.,

SEND

\$RECID

PROBM= .679, .639, .622, .597, .533, .487, .336,  
 PROBF= .440, .473, .468, .443, .334, .297, .177,  
 DELPRO=1040., 1379., 1595., 1868., 2192., 2423., 4615.,  
 DELFI= 1040., 1066., 1051., 1174., 1339., 1591., 2354.,  
 DELDIS=1066., 1116., 1087., 1141., 1458., 1688., 2707.,  
 DELPAR= 540., 911., 1044., 965., 1361., 1418., 2516.,  
 DELPRI= 940., 846., 868., 1008., 911., 1148., 1559.,  
 SEND

# Forecasting Function

```

C*****
C
C      FUNCTION FORECAST (MONTH, ICRIME)
C
C      THIS FUNCTION DETERMINES THE VIRGIN ARREST RATE FOR MONTH AND
C      CRIME SPECIFIED.
C*****
C
C      REAL NCRIMES(7,14),A(7,14),THETA(7),THET12(7)
C      *, DIF12(7),PCLEAR(7),PVIRG(7)
C
C      DATA LMONTH/0/
C      DATA ISEED/60617/
C
C      DATA THETA/.806,.427,.519,.522,.393,.502,.719/
C      DATA THET12/0.,.825,.698,.738,.75,.714,.0 /
C      DATA DIF12/0.,.5*1.,.8./
C
C      DATA PCLEAR/.8,.27,.63,.18,.2,.15,.51/
C      DATA PVIRG/.244,.196,.245,.206,.218,.259,.427/
C
C      INITIAL VALUES OF FORECAST FUNCTIONS (BEGINNING JAN., '74)
C      DATA ((NCRIMES(I,J),J=1,14),I=1,7)/
C      *39.,33.,46.,38.,37.,40.,40.,35.,42.,35.,55.,47.,53.,8.,
C      *1318.,1111.,1059.,1058.,1067.,999.,1058.,1098.,1025.,
C      * 1168.,1369.,1488.,1295.,8.,
C      *1255.,1100.,1302.,1327.,1387.,1452.,1456.,1378.,1430.,
C      * 1366.,1395.,1183.,1218.,8.,
C      *6887.,5189.,5706.,5474.,5406.,5306.,5486.,5367.,5365.,
C      * 6138.,5775.,6588.,6918.,8.,
C      *7426.,6982.,7474.,6839.,7123.,6805.,7058.,7201.,6928.,
C      * 7733.,7581.,7941.,8479.,8.,
C      *2789.,2580.,2673.,2585.,2529.,2485.,2456.,2562.,2557.,
C      * 2761.,2827.,2772.,2731.,8.,
C      *184.,164.,170.,139.,153.,167.,166.,177.,184.,184.,
C      * 164.,163.,140.,8./
C
C      VALUES OF INITIAL FORECAST ERRORS
C      DATA ((A(I,J),J=1,14),I=1,7)/
C      *14*0.,
C      *51.6,140.5,-213.7,257.5,52.0,99.3,-15.2,35.4,267.8,2.7,
C      * 224.3,26.5,-22.4,8.,
C      *48.5,-120.7,-21.7,79.8,-32.7,23.2,-58.7,-8.9,52.8,-51.9,
C      * 113.0,-168.1,78.8,0.,
C      *171.9,-722.1,-204.4,225.8,-45.4,168.6,-7.5,3369.5,189.6,466.6,
C      * -105.6,476.6,652.8,8.,
C      *128.6,-286.2,173.5,-203.9,266.5,27.8,87.6,304.2,26.3,
C      * 286.6,144.1,123.3,690.9,8.,
C      *13.1,-69.1,-123.2,-23.3,56.1,37.6,-141.1,25.8,121.2,
C      * 89.9,4.8,31.8,88.4,8.,
C      *1498./

```

```

C
C   DETERMINE TIME INDICES
C   IF(MONTH .EQ. LMONTH) GO TO 1
C   IMONTH=MONTH+13
C   IPER=MOD(IMONTH,14)
C   IF(IPER.EQ.0)IPER=14
C   IPER1=IPER-1
C   IF(IPER1.EQ.0)IPER1=14
C   IPERA1=IPER1
C   IF(MONTH.GT.1) IPERA1=14
C   IPER2=IPER+2
C   IF(IPER2.GE.15)IPER2=IPER-12
C   IPERA2=IPER2
C   IF(MONTH.GT.12) IPERA2=14
C   IPER3=IPER+1
C   IF(IPER3.GE.15)IPER3=IPER-13
C   IPERA3=IPER3
C   IF(MONTH.GT.13) IPERA3=14
C   LMONTH=MONTH
C
C   FORECAST NUMBER OF OCCURANCES OF EACH CRIME TYPE
C   1 NCRIMES(ICRIME,IPER) = NCRIMES(ICRIME,IPER1)
C     * +DIF12(ICRIME) * (NCRIMES(ICRIME,IPER2)-NCRIMES(ICRIME,IPER3))
C     * +THETA(ICRIME)*A(ICRIME,IPERA1)
C     * +THET12(ICRIME)*(A(ICRIME,IPERA2)+THETA(ICRIME)*A(ICRIME,IPERA3))
C
C   DETERMINE TOTAL ARRESTS
C   ARRESTS=PCLEAR(ICRIME)*NCRIMES(ICRIME,IPER)
C
C   DETERMINE VIRGIN ARREST RATE
C   FORCAST=PVIRG(ICRIME)*ARRESTS
C
C   SCALE FORECASTS
C   FORCAST=FORCAST/30.
C   IF(FORCAST.GE.1) RETURN
C   B=RAND(ISEED)
C   FORCAST=1.00
C   IF(B.GT.FORCAST) FORCAST=B.
C
C   RETURN
C   END

```

## APPENDIX C

### SAMPLE OUTPUT

The output contained in this appendix is representative of the types of statistics and graphical analysis that are produced by the model developed for this research. For example, the queueing time series shown are for only one processor in the CJS network and the offender analysis is restricted to male career criminals. Reports are also output for other processors and for all other offender categories as well, but for brevity they are not reproduced here.



TRACE THE EXECUTION OF RUN 1												
AT MONTH	2	RESOURCE USAGE:	14.	7.	2.	8.	4.	67.	442.	911.	9.	2.
AT MONTH	2	PRE-TRIAL QUEUE:	8.									
AT MONTH	2	MAX. RESOURCE LEVELS:	24.	9999.	3.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	3	RESOURCE USAGE:	15.	6.	1.	12.	5.	66.	427.	894.	7.	4.
AT MONTH	3	PRE-TRIAL QUEUE:	8.									
AT MONTH	3	MAX. RESOURCE LEVELS:	24.	9999.	3.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	4	RESOURCE USAGE:	21.	7.	1.	13.	3.	67.	438.	879.	8.	6.
AT MONTH	4	PRE-TRIAL QUEUE:	8.									
AT MONTH	4	MAX. RESOURCE LEVELS:	24.	9999.	3.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	5	RESOURCE USAGE:	24.	4.	1.	8.	4.	67.	488.	883.	10.	2.
AT MONTH	5	PRE-TRIAL QUEUE:	9.									
AT MONTH	5	MAX. RESOURCE LEVELS:	24.	9999.	3.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	6	RESOURCE USAGE:	24.	8.	2.	11.	8.	68.	399.	891.	11.	5.
AT MONTH	6	PRE-TRIAL QUEUE:	8.									
AT MONTH	6	MAX. RESOURCE LEVELS:	26.	9999.	3.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	7	RESOURCE USAGE:	26.	7.	3.	15.	10.	67.	391.	899.	16.	5.
AT MONTH	7	PRE-TRIAL QUEUE:	12.									
AT MONTH	7	MAX. RESOURCE LEVELS:	26.	9999.	3.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	418	RESOURCE USAGE:	36.	9.	2.	38.	6.	129.	684.	1367.	24.	5.
AT MONTH	418	PRE-TRIAL QUEUE:	8.									
AT MONTH	418	MAX. RESOURCE LEVELS:	62.	9999.	7.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	419	RESOURCE USAGE:	52.	4.	3.	22.	17.	135.	679.	1383.	24.	6.
AT MONTH	419	PRE-TRIAL QUEUE:	8.									
AT MONTH	419	MAX. RESOURCE LEVELS:	63.	9999.	7.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	420	RESOURCE USAGE:	63.	7.	5.	23.	16.	137.	675.	1388.	26.	5.
AT MONTH	420	PRE-TRIAL QUEUE:	8.									
AT MONTH	420	MAX. RESOURCE LEVELS:	63.	9999.	7.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	421	RESOURCE USAGE:	48.	9.	7.	38.	12.	136.	678.	1369.	38.	6.
AT MONTH	421	PRE-TRIAL QUEUE:	13.									
AT MONTH	421	MAX. RESOURCE LEVELS:	63.	9999.	7.	9999.	9999.	9999.	9999.	9999.	9999.	9999.
AT MONTH	422	RESOURCE USAGE:	58.	7.	7.	37.	15.	134.	668.	1377.	26.	15.
AT MONTH	422	PRE-TRIAL QUEUE:	9.									
AT MONTH	422	MAX. RESOURCE LEVELS:	63.	9999.	7.	9999.	9999.	9999.	9999.	9999.	9999.	9999.

AT TIME 19835.00 SIMULATION RUN SUCCESSFULLY TERMINATES WITH 18375 SINK NODES REALIZED SINCE TIME TL = 20.00

THE TOTAL NUMBER OF FIRST-OFFENSE ARRESTS AFTER 20.00 IS 20724  
 THE TOTAL NUMBER OF RECIDIVIST ARRESTS AFTER 20.00 IS 20597

FOR CRIME 1 ( HOMICIDE ):	422 FIRST-OFFENSE ARRESTS AND	246 RECIDIVIST ARRESTS ARE MADE
FOR CRIME 2 ( ROBBERY ):	1512 FIRST-OFFENSE ARRESTS AND	663 RECIDIVIST ARRESTS ARE MADE
FOR CRIME 3 ( ASSAULT ):	4630 FIRST-OFFENSE ARRESTS AND	2671 RECIDIVIST ARRESTS ARE MADE
FOR CRIME 4 ( BURGLARY ):	4760 FIRST-OFFENSE ARRESTS AND	2134 RECIDIVIST ARRESTS ARE MADE
FOR CRIME 5 ( C. LARCENY ):	7427 FIRST-OFFENSE ARRESTS AND	6882 RECIDIVIST ARRESTS ARE MADE
FOR CRIME 6 ( AUTO THEFT ):	1591 FIRST-OFFENSE ARRESTS AND	4899 RECIDIVIST ARRESTS ARE MADE
FOR CRIME 7 ( RAPE ):	422 FIRST-OFFENSE ARRESTS AND	3866 RECIDIVIST ARRESTS ARE MADE

NOTE: RESOURCE STATISTICS ARE GIVEN FOR EACH OF THE 10 RESOURCE TYPES  
 USED IN THE MODEL. THE PRE-TRIAL QUEUE IS THE NUMBER OF OFFENDERS  
 WAITING FOR SERVICE AT BOXES 37 and 39 OF THE SUPERIOR COURT.

#### TIME AND COST STATISTICS ####

STAT. TYPE	NO. OF OBS.	MEAN
TOTAL COST	1	1304097117.031

#### GROUP COST STATISTICS ####

GRP NO.	MEAN	COST %	TIME SHOT NO.
1	169482469.517	12.996	POLICE
2	95102006.769	7.293	JUVENILE COURT
3	162985098.527	12.498	JUVENILE CORRECTIONS
4	307180326.279	23.555	PROSECUTION & PRE-TRIAL HEARINGS
5	186143384.173	14.274	LOWER & SUPERIOR COURTS
6	347026630.337	26.610	CORRECTIONS
7	36177201.752	2.774	PRE-TRIAL DETENTION

## #### RESOURCE STATISTICS ####

RESC NO.	STAT. TYPE	LEVEL	MEAN
1	EXP UTLZ	63	29.302
1	OVERDMND	63	0.000
1	COST	63	247026565.511
1	COST %		18.942
2	EXP UTLZ	99999	2.131
2	OVERDMND	99999	0.000
2	COST	99999	169482469.482
2	COST %		12.996
3	EXP UTLZ	7	2.981
3	OVERDMND	7	0.000
3	COST	7	91651951.807
3	COST %		7.028
4	EXP UTLZ	99999	18.496
4	OVERDMND	99999	0.000
4	COST	99999	123276172.082
4	COST %		9.453
5	EXP UTLZ	99999	7.747
5	OVERDMND	99999	0.000
5	COST	99999	72842660.317
5	COST %		5.586
6	EXP UTLZ	99999	79.773
6	OVERDMND	99999	0.000
6	COST	99999	162985098.473
6	COST %		12.498
7	EXP UTLZ	99999	442.023
7	OVERDMND	99999	0.000
7	COST	99999	175359344.900
7	COST %		13.447
8	EXP UTLZ	99999	865.433
8	OVERDMND	99999	0.000
8	COST	99999	171667285.343
8	COST %		13.164
9	EXP UTLZ	99999	12.578
9	OVERDMND	99999	0.000
9	COST	99999	36177201.741
9	COST %		2.774
10	EXP UTLZ	99999	4.970
10	OVERDMND	99999	0.000
10	COST	99999	53628367.387
10	COST %		4.112

00000 TIME SHOT NUMBER 43 00000

TIME	VALUE	CUMULATIVE TOTAL CJS COST
		0 32955.00 65910.00 98865.00 131820.00
360.00	66414.000	.
720.00	47616.000	.
1080.00	54344.000	.
1440.00	53764.000	.
1800.00	58482.000	.
2160.00	65877.000	.
2520.00	71736.000	.
2880.00	61724.000	.
3240.00	68001.000	.
3600.00	68283.000	.
3960.00	62321.000	.
4320.00	78978.000	.
4680.00	76524.000	.
5040.00	74713.000	.
5400.00	75092.000	.
5760.00	79109.000	.
6120.00	65093.000	.
6480.00	69307.000	.
6840.00	69489.000	.
7200.00	78719.000	.
7560.00	71807.000	.
7920.00	69175.000	.
8280.00	77724.000	.
8640.00	78931.000	.
9000.00	88050.000	.
9360.00	89398.000	.
9720.00	76863.000	.
10080.00	813925.000	.
10440.00	75523.000	.
10800.00	85240.000	.
11160.00	94094.000	.
11520.00	91562.000	.
11880.00	93610.000	.
12240.00	82292.000	.
12600.00	95694.000	.
12960.00	99022.000	.
13320.00	183205.000	.
13680.00	94917.000	.
14040.00	95214.000	.
14400.00	181899.000	.
14760.00	92697.000	.
15120.00	185690.000	.
15480.00	111222.000	.
15840.00	102512.000	.
16200.00	189550.000	.
16560.00	127165.000	.
16920.00	111772.000	.
17280.00	112243.000	.
17640.00	121842.000	.
18000.00	113507.000	.
18360.00	128457.000	.
18720.00	110436.000	.
19080.00	126394.000	.
19440.00	117218.000	.
19800.00	131820.000	.

## ### QUE STATISTICS ###

QUE NO.	STAT. TYPE	MEAN
5	NUMB BUSY SERVER	2.131
5	QUEUE LENGTH	0.000
5	SYSTM LINE LGTH	2.131
5	WAITING TIME	0.000
5	BUSY %	84.419
5	NUMBER BALKED	0.000
5	ENTITIES PASSED	42307.000
5	COST	169482469.517
5	COST %	12.996
8	NUMB BUSY SERVER	9.515
8	QUEUE LENGTH	0.000
8	SYSTM LINE LGTH	9.515
8	WAITING TIME	0.000
8	BUSY %	99.867
8	NUMBER BALKED	0.000
8	ENTITIES PASSED	5053.000
8	COST	63415875.325
8	COST %	4.863
9	NUMB BUSY SERVER	4.754
9	QUEUE LENGTH	0.000
9	SYSTM LINE LGTH	4.754
9	WAITING TIME	0.000
9	BUSY %	98.466
9	NUMBER BALKED	0.000
9	ENTITIES PASSED	2534.000
9	COST	31686131.445
9	COST %	2.430
.	.	.
.	.	.
.	.	.
37	NUMB BUSY SERVER	.372
37	QUEUE LENGTH	3.784
37	SYSTM LINE LGTH	4.156
37	WAITING TIME	6.106
37	BUSY %	31.773
37	NUMBER BALKED	0.000
37	ENTITIES PASSED	12286.000
37	COST	14560132.618
37	COST %	1.116
39	NUMB BUSY SERVER	2.609
39	QUEUE LENGTH	1.581
39	SYSTM LINE LGTH	4.190
39	WAITING TIME	7.183
39	BUSY %	92.456
39	NUMBER BALKED	0.000
39	ENTITIES PASSED	4354.000
39	COST	130378584.526
39	COST %	9.998
.	.	.
.	.	.
.	.	.
.	.	.

#### TIME SHOT NUMBER 25 ####

TIME	VALUE	AVERAGE NUMBER OF BUSY SERVERS (BOX 39)				
		0	1.50	3.00	4.50	6.00
360.00	2.000	.....	.....	.....	.....	.....
720.00	2.000	.....	.....	.....	.....	.....
1080.00	1.000	.....	.....	.....	.....	.....
1440.00	1.000	.....	.....	.....	.....	.....
1800.00	1.000	.....	.....	.....	.....	.....
2160.00	2.000	.....	.....	.....	.....	.....
2520.00	3.000	.....	.....	.....	.....	.....
2880.00	3.000	.....	.....	.....	.....	.....
3240.00	2.000	.....	.....	.....	.....	.....
3600.00	3.000	.....	.....	.....	.....	.....
3960.00	0.000	.....	.....	.....	.....	.....
4320.00	3.000	.....	.....	.....	.....	.....
4680.00	3.000	.....	.....	.....	.....	.....
5040.00	2.000	.....	.....	.....	.....	.....
5400.00	2.000	.....	.....	.....	.....	.....
5760.00	1.000	.....	.....	.....	.....	.....
6120.00	3.000	.....	.....	.....	.....	.....
6480.00	1.000	.....	.....	.....	.....	.....
6840.00	0.000	.....	.....	.....	.....	.....
7200.00	2.000	.....	.....	.....	.....	.....
7560.00	0.000	.....	.....	.....	.....	.....
7920.00	1.000	.....	.....	.....	.....	.....
8280.00	1.000	.....	.....	.....	.....	.....
8640.00	3.000	.....	.....	.....	.....	.....
9000.00	3.000	.....	.....	.....	.....	.....
9360.00	3.000	.....	.....	.....	.....	.....
9720.00	2.000	.....	.....	.....	.....	.....
10080.00	3.000	.....	.....	.....	.....	.....
10440.00	2.000	.....	.....	.....	.....	.....
10800.00	3.000	.....	.....	.....	.....	.....
11160.00	3.000	.....	.....	.....	.....	.....
11520.00	4.000	.....	.....	.....	.....	.....
11880.00	1.000	.....	.....	.....	.....	.....
12240.00	1.000	.....	.....	.....	.....	.....
12600.00	4.000	.....	.....	.....	.....	.....
12960.00	4.000	.....	.....	.....	.....	.....
13320.00	4.000	.....	.....	.....	.....	.....
13680.00	4.000	.....	.....	.....	.....	.....
14040.00	4.000	.....	.....	.....	.....	.....
14400.00	2.000	.....	.....	.....	.....	.....
14760.00	4.000	.....	.....	.....	.....	.....
15120.00	5.000	.....	.....	.....	.....	.....
15480.00	0.000	.....	.....	.....	.....	.....
15840.00	3.000	.....	.....	.....	.....	.....
16200.00	4.000	.....	.....	.....	.....	.....
16560.00	2.000	.....	.....	.....	.....	.....
16920.00	3.000	.....	.....	.....	.....	.....
17280.00	5.000	.....	.....	.....	.....	.....
17640.00	6.000	.....	.....	.....	.....	.....
18000.00	3.000	.....	.....	.....	.....	.....
18360.00	6.000	.....	.....	.....	.....	.....
18720.00	6.000	.....	.....	.....	.....	.....
19080.00	5.000	.....	.....	.....	.....	.....
19440.00	6.000	.....	.....	.....	.....	.....
19800.00	6.000	.....	.....	.....	.....	.....

00000 TIME SHOT NUMBER 25 00000

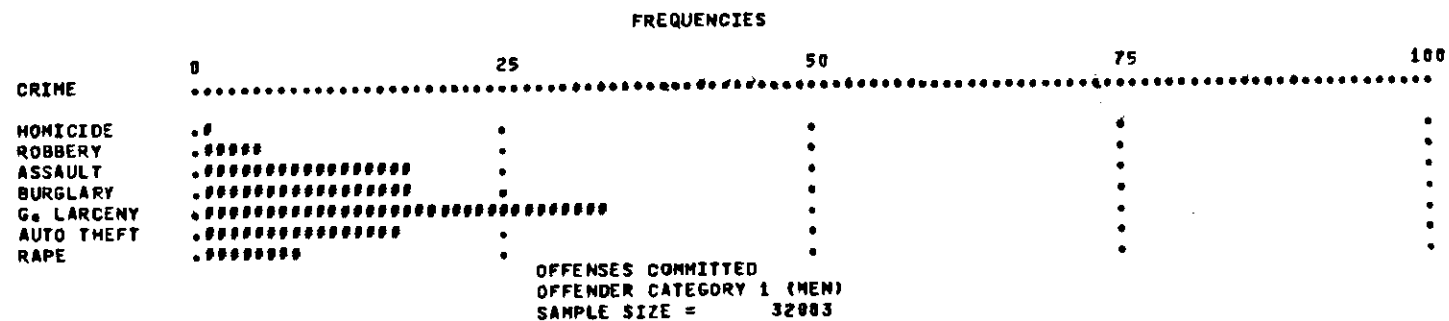
TIME	VALUE	AVERAGE QUEUE LENGTH (BOX 39)				
		0	1.50	3.00	4.50	6.00
360.00	0.000	.	.	.	.	.
720.00	0.000	.	.	.	.	.
1080.00	0.000	.	.	.	.	.
1440.00	0.000	.	.	.	.	.
1800.00	0.000	.	.	.	.	.
2160.00	0.000	.	.	.	.	.
2520.00	2.000	.....	.....	.	.	.
2880.00	3.000	.....	.....	.....	.	.
3240.00	0.000	.	.	.	.	.
3600.00	0.000	.	.	.	.	.
3960.00	0.000	.	.	.	.	.
4320.00	1.000	.....	.....	.	.	.
4680.00	3.000	.....	.....	.....	.	.
5040.00	2.000	.....	.....	.	.	.
5400.00	0.000	.	.	.	.	.
5760.00	0.000	.	.	.	.	.
6120.00	3.000	.....	.....	.....	.	.
6480.00	0.000	.	.	.	.	.
6840.00	1.000	.....	.....	.	.	.
7200.00	0.000	.	.	.	.	.
7560.00	0.000	.	.	.	.	.
7920.00	1.000	.....	.....	.	.	.
8280.00	0.000	.	.	.	.	.
8640.00	0.000	.	.	.	.	.
9000.00	1.000	.....	.....	.....	.	.
9360.00	1.000	.....	.....	.	.	.
9720.00	0.000	.	.	.	.	.
10080.00	2.000	.....	.....	.	.	.
10440.00	0.000	.	.	.	.	.
10800.00	4.000	.....	.....	.....	.	.
11160.00	2.000	.....	.....	.	.	.
11520.00	1.000	.....	.....	.	.	.
11880.00	0.000	.	.	.	.	.
12240.00	0.000	.	.	.	.	.
12600.00	5.000	.....	.....	.....	.....	.
12960.00	5.000	.....	.....	.....	.....	.
13320.00	0.000	.	.	.	.	.
13680.00	3.000	.....	.....	.....	.	.
14040.00	6.000	.....	.....	.....	.....	.
14400.00	0.000	.	.	.	.	.
14760.00	2.000	.....	.....	.	.	.
15120.00	3.000	.....	.....	.....	.	.
15480.00	0.000	.	.	.	.	.
15840.00	0.000	.	.	.	.	.
16200.00	3.000	.....	.....	.....	.	.
16560.00	0.000	.	.	.	.	.
16920.00	1.000	.....	.....	.	.	.
17280.00	3.000	.....	.....	.....	.	.
17640.00	5.000	.....	.....	.....	.....	.
18000.00	0.000	.	.	.	.	.
18360.00	2.000	.....	.....	.	.	.
18720.00	0.000	.	.	.	.	.
19080.00	2.000	.....	.....	.	.	.
19440.00	0.000	.	.	.	.	.
19800.00	4.000	.....	.....	.....	.	.

00000 TIME SHOT NUMBER 27 00000

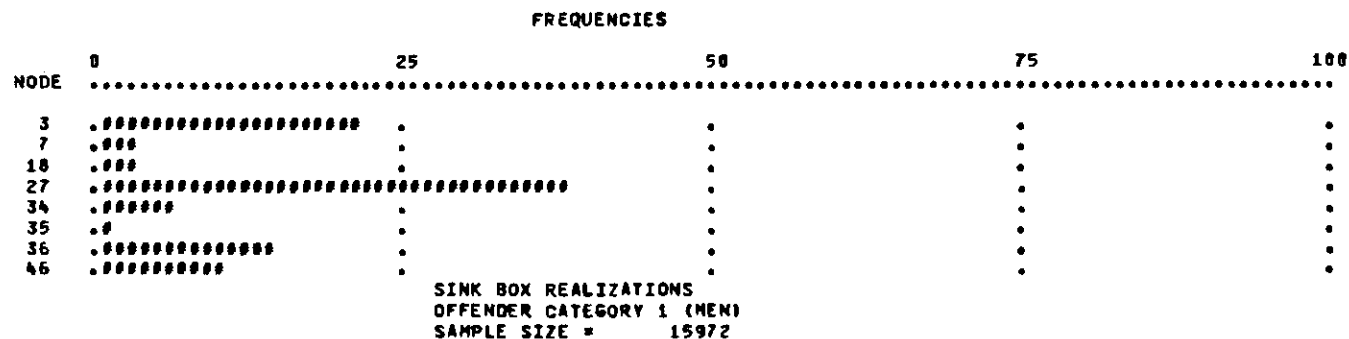
TIME	VALUE	AVERAGE RESOURCE COST (BOX 39)			
		0	3776.50	7557.00	11335.50
					15114.00
360.00	5030.000	.....			
720.00	5030.000	.....			
1080.00	2519.000	.....			
1440.00	2519.000	.....			
1800.00	2519.000	.....			
2160.00	5030.000	.....			
2520.00	7557.000	.....			
2880.00	7557.000	.....			
3240.00	5030.000	.....			
3600.00	7557.000	.....			
3960.00	0.000	.....			
4320.00	7557.000	.....			
4680.00	7557.000	.....			
5040.00	5030.000	.....			
5400.00	5030.000	.....			
5760.00	2519.000	.....			
6120.00	7557.000	.....			
6480.00	2519.000	.....			
6840.00	0.000	.....			
7200.00	5030.000	.....			
7560.00	0.000	.....			
7920.00	2519.000	.....			
8280.00	2519.000	.....			
8640.00	7557.000	.....			
9000.00	7557.000	.....			
9360.00	7557.000	.....			
9720.00	5030.000	.....			
10080.00	7557.000	.....			
10440.00	5030.000	.....			
10800.00	7557.000	.....			
11160.00	7557.000	.....			
11520.00	10076.000	.....			
11880.00	2519.000	.....			
12240.00	2519.000	.....			
12600.00	10076.000	.....			
12960.00	10076.000	.....			
13320.00	10076.000	.....			
13680.00	10076.000	.....			
14040.00	10076.000	.....			
14400.00	5030.000	.....			
14760.00	10076.000	.....			
15120.00	12595.000	.....			
15480.00	0.000	.....			
15840.00	7557.000	.....			
16200.00	10076.000	.....			
16560.00	5030.000	.....			
16920.00	7557.000	.....			
17280.00	12595.000	.....			
17640.00	15114.000	.....			
18000.00	7557.000	.....			
18360.00	15114.000	.....			
18720.00	15114.000	.....			
19080.00	12595.000	.....			
19440.00	15114.000	.....			
19800.00	15114.000	.....			



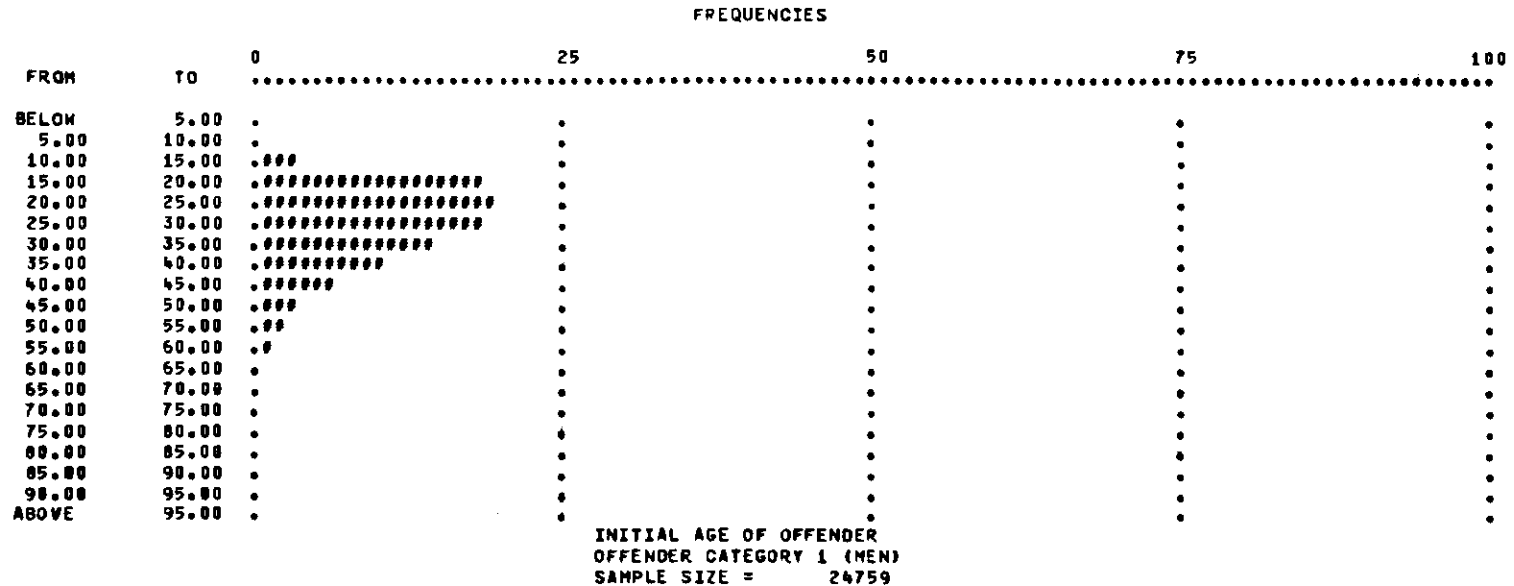
##### FREQUENCY HISTOGRAM #####



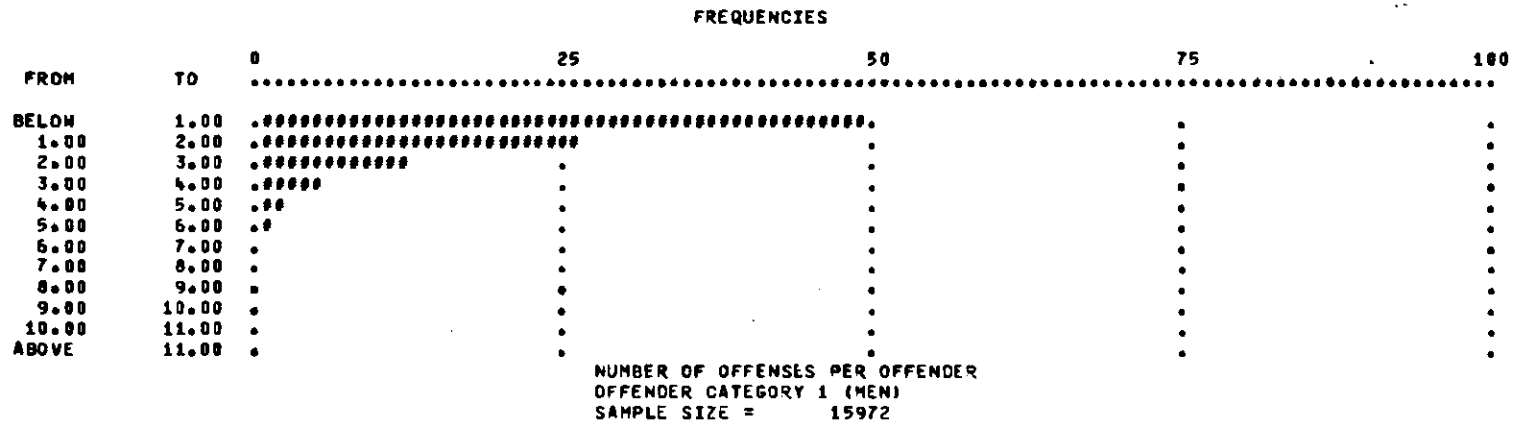
##### FREQUENCY HISTOGRAM #####



##### FREQUENCY HISTOGRAM #####

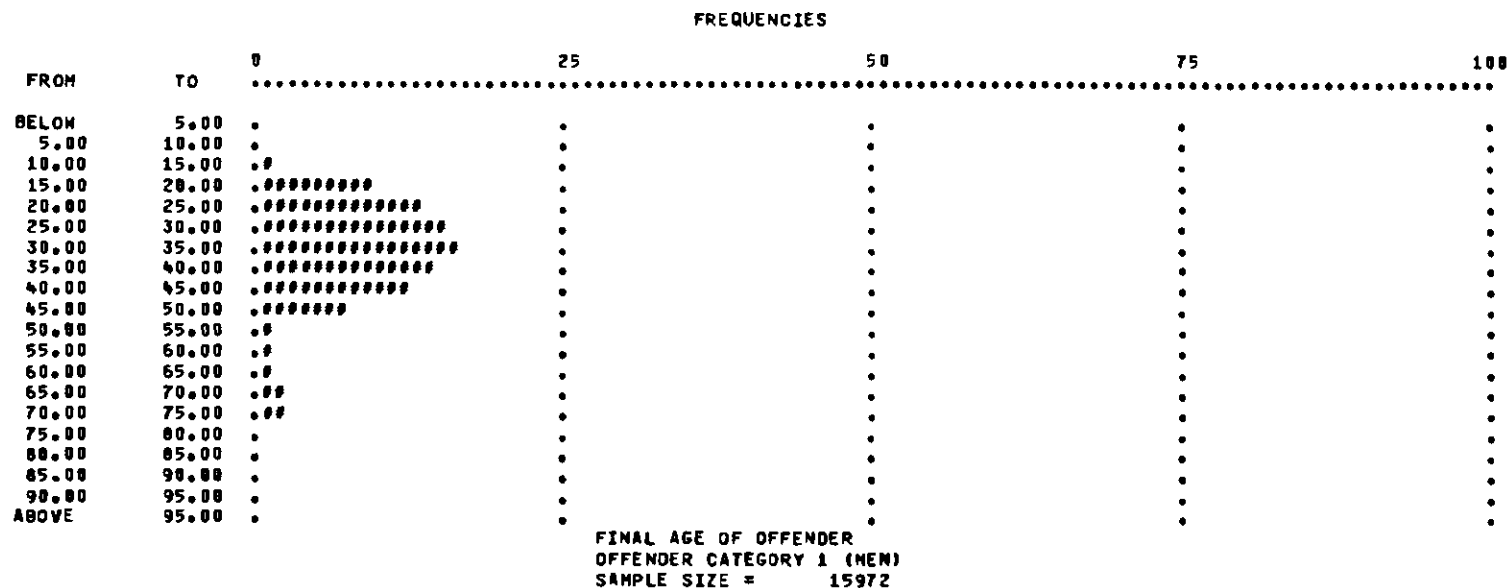


##### FREQUENCY HISTOGRAM #####

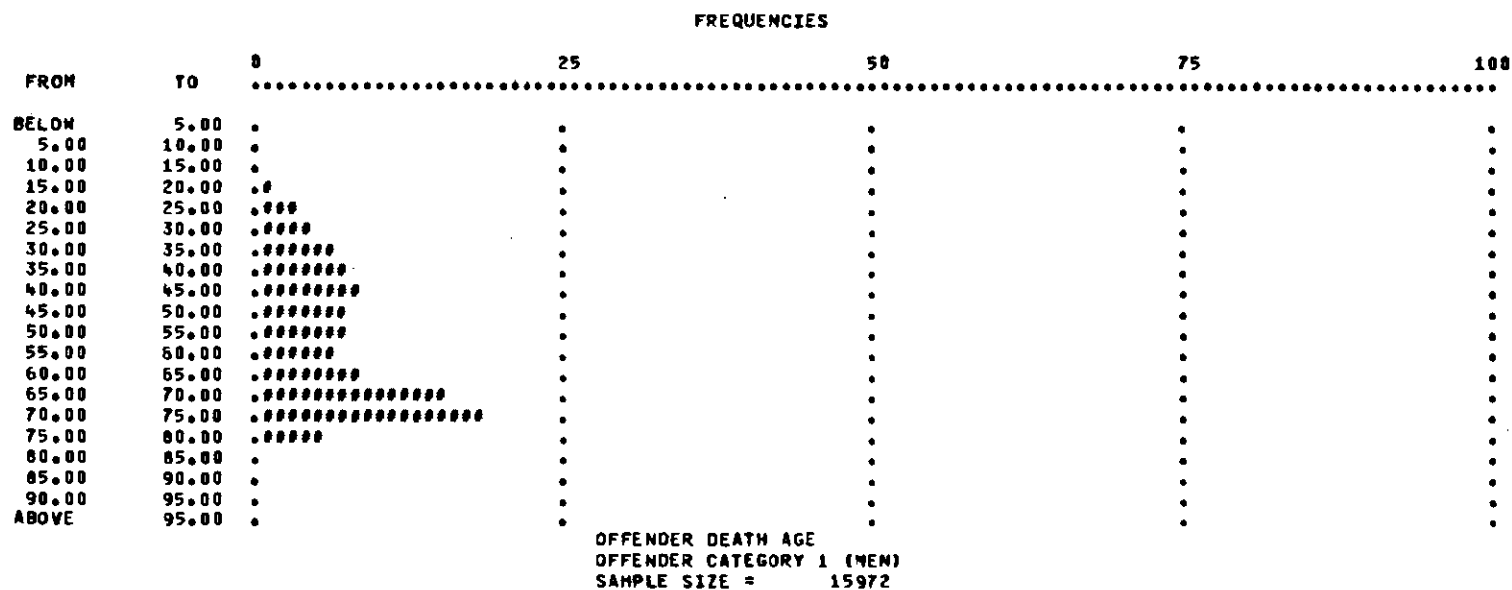


AVERAGE NUMBER OF OFFENSES WHEN LAST CRIME IS HOMICIDE	=	1.95	N =	303
AVERAGE NUMBER OF OFFENSES WHEN LAST CRIME IS ROBBERY	=	1.69	N =	888
AVERAGE NUMBER OF OFFENSES WHEN LAST CRIME IS ASSAULT	=	1.69	N =	2822
AVERAGE NUMBER OF OFFENSES WHEN LAST CRIME IS BURGLARY	=	1.59	N =	2743
AVERAGE NUMBER OF OFFENSES WHEN LAST CRIME IS G. LARCENY	=	1.98	N =	5282
AVERAGE NUMBER OF OFFENSES WHEN LAST CRIME IS AUTO THEFT	=	2.42	N =	2503
AVERAGE NUMBER OF OFFENSES WHEN LAST CRIME IS RAPE	=	2.99	N =	1431

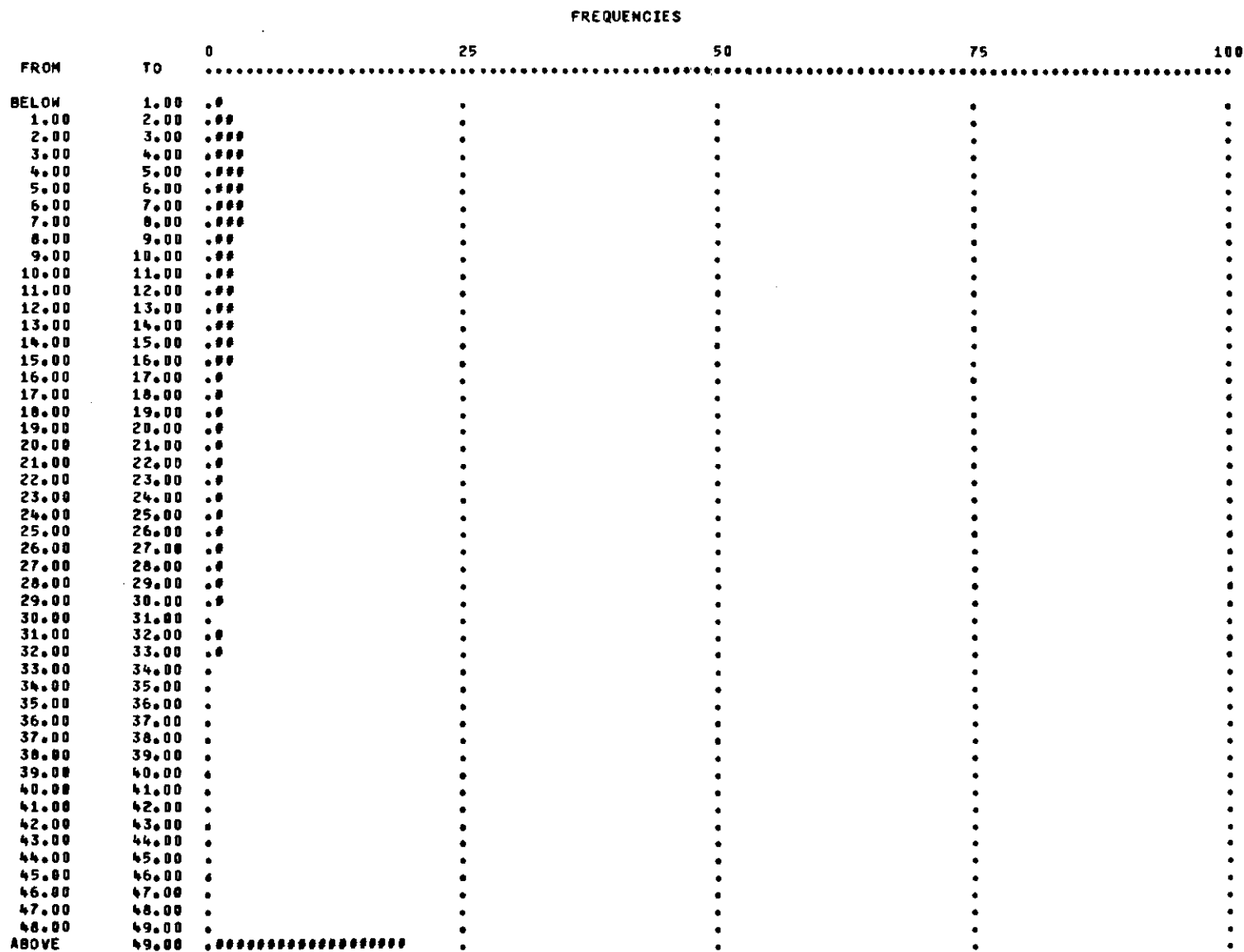
#### FREQUENCY HISTOGRAM ####



#### FREQUENCY HISTOGRAM ####



#### FREQUENCY HISTOGRAM ####



26. CAREER CRIMINAL COST / 1500  
 OFFENDER CATEGORY 1 (MEN)  
 SAMPLE SIZE = 15972

0000 TIME SHOT 0000

TIME	VALUE	AVERAGE RECORDED VALUE				
		0	13639.45	27278.89	48916.34	54887.79
7300.00	42891.134					
7500.00	45700.567					
7700.00	39119.534					
7900.00	42263.446					
8100.00	40026.123					
8300.00	44994.353					
8500.00	46166.100					
8700.00	47438.045					
8900.00	52047.398					
9100.00	52007.204					
9300.00	53506.073					
9500.00	41140.426					
9700.00	40329.193					
9900.00	44227.664					
10100.00	47721.020					
10300.00	38797.461					
10500.00	53599.991					
10700.00	42626.620					
10900.00	49355.351					
11100.00	40358.120					
11300.00	47760.542					
11500.00	40470.373					
11700.00	46242.459					
11900.00	46147.651					
12100.00	46753.837					
12300.00	48545.072					
12500.00	54429.079					
12700.00	42653.208					
12900.00	47762.570					
13100.00	50502.017					
13300.00	46742.311					
13500.00	47524.973					
13700.00	40359.440					
13900.00	51200.010					
14100.00	45770.662					
14300.00	46631.304					
14500.00	43051.731					
14700.00	41934.115					
14900.00	46700.821					
15100.00	49210.427					
15300.00	44845.514					
15500.00	49497.085					
15700.00	46142.365					
15900.00	43631.176					
16100.00	50161.826					
16300.00	41945.422					
16500.00	51040.741					
16700.00	50935.492					
16900.00	45430.976					
17100.00	49920.361					
17300.00	49526.791					
17500.00	34557.760					
17700.00	43062.340					
17900.00	48654.050					
18100.00	50094.564					
18300.00	49611.411					
18500.00	50432.754					
18700.00	50774.423					
18900.00	43406.920					
19100.00	42575.602					
19300.00	43927.344					
19500.00	50309.674					
19700.00	43369.013					
19900.00	44908.846					
20100.00	46060.344					
20300.00	42849.747					
20500.00	47247.431					
20700.00	47557.033					
20900.00	46531.730					
21100.00	50063.575					

TIME SERIES OF CAREER CRIMINAL COST  
OFFENDER CATEGORY 1 (MEN)

00000 TIME SHOT 00000

TIME	VALUE	AVERAGE RECORDED VALUE				
		0	.55	1.10	1.65	2.21
7300.00	1.770					
7500.00	1.900					
7700.00	1.660					
7900.00	1.816					
8100.00	1.743					
8200.00	1.053					
8400.00	1.825					
8600.00	1.738					
8800.00	1.990					
9000.00	1.843					
9100.00	2.020					
9300.00	2.005					
9500.00	2.099					
9700.00	1.952					
9900.00	2.041					
10000.00	1.897					
10200.00	2.012					
10400.00	1.980					
10600.00	1.907					
10800.00	1.869					
10900.00	1.797					
11000.00	1.842					
11200.00	2.005					
11500.00	1.973					
11700.00	2.195					
11800.00	1.607					
12000.00	2.170					
12200.00	1.910					
12400.00	2.000					
12600.00	2.069					
12700.00	1.966					
12900.00	1.857					
13100.00	1.867					
13300.00	2.157					
13500.00	2.029					
13600.00	2.813					
13650.00	2.090					
14000.00	1.975					
14200.00	2.812					
14400.00	2.174					
14500.00	1.858					
14700.00	2.162					
14900.00	2.153					
15100.00	1.966					
15300.00	2.036					
15400.00	1.924					
15600.00	2.045					
15800.00	2.209					
16000.00	2.012					
16200.00	2.074					
16300.00	1.937					
16500.00	2.120					
16700.00	2.087					
16900.00	2.162					
17100.00	2.151					
17200.00	2.111					
17400.00	2.109					
17600.00	2.035					
17800.00	2.053					
18000.00	1.842					
18100.00	2.060					
18300.00	2.033					
18500.00	2.160					
18700.00	2.010					
18900.00	2.092					
19000.00	2.045					
19200.00	1.969					
19400.00	2.010					
19600.00	2.103					
19800.00	2.167					

TIME SERIES OF NUMBER OF OFFENSES PER OFFENDER  
OFFENDER CATEGORY 1 (MEN)

\*\*\*\*\* TIME SHOT \*\*\*\*\*

TIME	VALUE	AVERAGE RECORDED VALUE
		0 7172.62 14345.24 21517.87 28698.49
7380.00	24229.728	
7560.00	25278.126	
7740.00	23560.620	
7920.00	23211.064	
8100.00	22968.810	
8280.00	24227.689	
8460.00	25410.651	
8640.00	27527.857	
8820.00	27353.159	
9000.00	24690.407	
9180.00	26526.439	
9360.00	28515.650	
9540.00	23115.977	
9720.00	22653.194	
9900.00	23379.174	
10080.00	20453.009	
10260.00	26640.472	
10440.00	21442.402	
10620.00	25354.619	
10800.00	21598.697	
10980.00	26593.451	
11160.00	21369.631	
11340.00	24859.242	
11520.00	23379.905	
11700.00	21296.250	
11880.00	24210.563	
12060.00	26385.421	
12240.00	22232.334	
12420.00	23381.245	
12600.00	24411.174	
12780.00	23535.356	
12960.00	25998.679	
13140.00	21614.297	
13320.00	23741.944	
13500.00	22561.442	
13680.00	24158.777	
13860.00	21525.865	
14040.00	21186.376	
14220.00	23220.447	
14400.00	22632.644	
14580.00	24243.899	
14760.00	23128.573	
14940.00	21433.269	
15120.00	22194.519	
15300.00	24637.747	
15480.00	21796.120	
15660.00	24955.251	
15840.00	23080.347	
16020.00	22342.649	
16200.00	24073.744	
16380.00	23509.817	
16560.00	25734.905	
16740.00	21874.840	
16920.00	22502.490	
17100.00	23249.184	
17280.00	23580.142	
17460.00	23911.356	
17640.00	24456.141	
17820.00	21146.961	
18000.00	23114.733	
18180.00	21531.690	
18360.00	24745.149	
18540.00	22544.672	
18720.00	22249.167	
18900.00	23471.374	
19080.00	20956.204	
19260.00	23758.353	
19440.00	23659.822	
19620.00	22128.423	
19800.00	23649.884	

TIME SERIES OF (CAREER COST)/(NUMBER OF OFFENSES)  
OFFENDER CATEGORY 1 (MEN)

00000 TIME SHOT 00000

TIME	VALUE	AVERAGE RECORDED VALUE				
		0	9.24	10.49	27.73	36.97
7300.00	36.490					
7500.00	33.000					
7700.00	33.120					
7900.00	32.710					
8100.00	33.013					
8300.00	35.201					
8500.00	36.777					
8700.00	36.400					
8900.00	36.205					
9100.00	35.116					
9300.00	36.667					
9500.00	36.016					
9700.00	35.795					
9900.00	36.797					
10100.00	36.976					
10300.00	33.436					
10500.00	35.035					
10700.00	36.506					
10900.00	36.950					
11100.00	36.103					
11300.00	31.986					
11500.00	35.720					
11700.00	35.632					
11900.00	33.675					
12100.00	35.631					
12300.00	33.410					
12500.00	36.201					
12700.00	36.552					
12900.00	35.451					
13100.00	36.927					
13300.00	36.845					
13500.00	36.533					
13700.00	36.774					
13900.00	35.071					
14100.00	36.096					
14300.00	36.500					
14500.00	36.495					
14700.00	36.300					
14900.00	36.920					
15100.00	36.945					
15300.00	36.593					
15500.00	36.457					
15700.00	36.971					
15900.00	36.800					
16100.00	33.979					
16300.00	35.403					
16500.00	36.051					
16700.00	36.994					
16900.00	36.249					
17100.00	36.038					
17300.00	36.500					
17500.00	35.217					
17700.00	35.607					
17900.00	36.444					
18100.00	36.906					
18300.00	36.127					
18500.00	35.167					
18700.00	36.140					
18900.00	35.550					
19100.00	32.543					
19300.00	36.772					
19500.00	35.633					
19700.00	35.109					
19900.00	35.267					
20100.00	33.432					
20300.00	35.545					
20500.00	36.529					
20700.00	35.733					
20900.00	36.636					
21100.00	35.078					

TIME SERIES OF AVERAGE AGE OF OFFENDER  
OFFENDER CATEGORY 1 (MEN)



## APPENDIX D

## CJS SUBROUTINE LISTINGS

```

C *****
C
C   SUBROUTINE USERB(KODE,D1,D2,D3,D4,D5,D6,D7,D8,D9,NRES,LOCRES,
C   *IFREQ,ATTRIB,TS,IATTRIB)
C
C   PURPOSE:  TO INPUT SPECIAL USER SUPPLIED DATA
C             BEFORE SIMULATION BEGINS.
C *****
C
C   COMMON/CJS/NCRIME,CRIME,NCHARG,NDISP,NSDISP,DUMP,NPN,ADULT,NOC,
C   *MBEGIN,ACS,PRG,MEQUE,MERES,MESEV,MEHIS,MIS,MONTHS,IYEARS,
C   *DCCC,MICCC,SCCC,SNOFS,ICOF,TSTOP,TINITL,IERROR,ANO,TRACEF,
C   *ANDFS(4,7),NO(4,7),RSUM(10),RSQ(10),RMAX(10),RNUM,RTIME,SAGE
C   * ,RGROW(10),SINITQ
C   COMMON/BASE/ARRAY(50000),UDATA(3000)
C   COMMON/GLOBAL/C1,C2,C3,FSHOT,IR,IP,IGO,IFROM,ITS1,IFR1, IAVAIL,
C   *IDRUN, ITO, IRATE, ISTUP, IPRTY, ISPSEG, IFULL, ISP1, ISP8, ISP9,
C   *ISP10, ISP11, ISP12, ISP15, ISP21, IP1, IP2, IP3, IP4, IP5, IP6,
C   *IP7, IP8, IP9, IP10, IP11,ISEEO,ITOP,IP15F, IP15, IP16, IP17,
C   *IP18, IP19, IP20, IP21, IP22, IP23, IP24, JHALF, K, LOCR2,
C   *MAXAR, MAXUD, MAXIA, MAXID, MHST, MENTRY, MRES, MBOX,MRES1,
C   *MMRES, MDELET, MWORK, MV, MCELL, NQBOX,NFVAR,NST,
C   *NERR, NOWPAS, NPASS, NBOX, NGRP, NETRL, NTRACE, NCALL, NSINK,
C   *NQB1, NQB2, NSOUR, NDBOX, NRBOX, NATRIB, NCELL,TCALL,UTIME,
C   *ISM1, ISW2, ISW3, ISW4, ISW5, VAR1, VAR2, VAR3, VAR4, VAR5, LINE,
C   *NRATE, IWRITE, IPASS, KSUM,LTOP, TNOW, TLAST,
C   *NODMP, CONT, COST, END, NXTMOD,QUE, RESC, RESCHG, SEPR,
C   *STDEP, TMCOST, UIN, UDUT, UFORM, STCHG,NOPREH, LU1, LU2, LU3, LU4,
C   *LU5, LU6, LU7, LU8, LU9, LU10,LLAG, LLSEGM, LORS
C
C   LOGICAL LU1, LU2, LU3, LU4, LU5, LU6, LU7, LU8, LU9, LU10, LLAG,
C   *LLSEGM, LORS, DUMP, TRACEF
C   LOGICAL CONT, COST, END, NXTMOD,QUE, RESC, RESCHG, SEPR,
C   *STDEP, TMCOST, UIN, UDUT, UFORM, STCHG,NOPREH, NOOMP
C
C   INTEGER D1,D2,D3,D4,D5,D6,D7,D8,D9,SUBN
C   INTEGER NRES(D1,D4), IFREQ(D8,D9), LOCRES(D4,D5), IATTRIB(D2,D3),
C   *IA(50000), LOC(100), IUDATA(3000), NP(100)
C   INTEGER CRIME(7), IDARCS(7), DUM(20,2)
C
C   REAL ATTRIB(D2,D3), TS(D6,D7), A(50000)
C   REAL PROBM(7),PROBF(7),DELPRO(7),DELFI(7),DELDIS(7),
C   * DELPAR(7),DELPRI(7),ANO(7),SCRACH(200),ICOF(4),SCCC(4),SNOFS(4),
C   * SAGE(4)
C   REAL ARC(7,7),SWITCH(7,7),BARGAN(7,15),
C   * CONVIC(7,15),TDISP(15,7),TSOUR(15,4),PDISP(15,7),
C   *PSDUR(15,4),TBAR(7),SEVERE(7),DISPL(7,7),SDURL(7,4),
C   * TARC(7),DEMO(7,6,6),YJAIL(7),AJAIL(7),CJAIL(7),
C   *PPOP(7),ABAR(7),ASD(7),AMIN(7),AMAX(7),PRISONH(15),PRISONF(15),
C   *DPARDL(15),PVIOL(15)
C

```

```

      EQUIVALENCE (IA(1), A(1), ARRAY(1), LOC(1)),
      *          (UDATA(1), IUDATA(1), NP(1))
      EQUIVALENCE (SCRACH(1), DEMO(1,1,1), DUM(1,1), SWITCH(1,1),
      *          BARGAN(1,1), CONVIC(1,1), DISPL(1,1), PRISONM(1),
      *          PROBM(1))
      EQUIVALENCE (SCRACH(50), TBAR(1), ARC(1,1), SEVERE(1), SDURL(1,1),
      *          PRISONF(1), PROBF(1))
      EQUIVALENCE (SCRACH(60), DELPRO(1))
      EQUIVALENCE (SCRACH(70), DPAROL(1), DELFI(1))
      EQUIVALENCE (SCRACH(80), DELDIS(1))
      EQUIVALENCE (SCRACH(100), TARC(1), PVIOL(1), DELPAR(1))
      EQUIVALENCE (SCRACH(110), IDARCS(1), POISP(1,1), TOISP(1,1),
      *          DELPRI(1))
      EQUIVALENCE (SCRACH(220), PSDUR(1,1), TSOUR(1,1))

C
      DATA MAXARC/7/
      DATA SUBN/8HUSERB /

C
C
      NAMELISTS:
      NAMELIST/STIME/ID, TBAR
      NAMELIST/FLOUT/ID, NARC, IDARCS, ARC
      NAMELIST/PARAM/NCRIME, NCHARG, NDISP, NSOISP, DUMP, ISEED,
      *NOC, ADULT, NSBOX, NEBOX, MEQUE, MERES, MESEV, MEHIS, MIS,
      *PRG, ICCG, MICCC, TSTOP, TINITL, MBEGIN, TRACEF, RTIME, RGROW, SINITQ
      NAMELIST/CRIMES/SWITCH, SEVERE, ANO, YJAIL, AJAIL, CJAIL, TSEVER
      NAMELIST/OFFENDR/CAT, PPOP, ABAR, ASD, AMIN, AMAX
      NAMELIST/PLEA/BARGAN, POISP, PSDUR
      NAMELIST/COURT/CONVIC, TOISP, TSOUR
      NAMELIST/LCOURT/DISPL, SDURL
      NAMELIST/PAROLE/PRISONM, PRISONF, DPAROL, PVIOL
      NAMELIST/RECID/PROBM, PROBF, DELPRO, DELFI, DELDIS, DELPAR, DELPRI

C
C
      IF(KODE.EQ.2)GO TO 1

C
C
      #####
      SAVE DIMENSIONS OF CERTAIN GNS ARRAYS
      #####

C
      IF(KODE.NE.1)CALL ERRIN(0,0,8HUSERB ,8HILLEGAL ,
      * 8HSUBROUTI,8HNE CALL ,8H      ), RETURNS(9000,9000)
      D6=ITS1
      D7=NCELL
      D8=IFR1
      D9=NCELL
      RETURN

C
C
      #####
      READ AND STORE USER DATA IN ARRAYS UDATA AND IUDATA
      #####

C
      READ CRIMINAL JUSTICE MODEL PARAMETERS
      1 DUMP=.FALSE.
      MEQUE=0
      MERES=0

```

```

MESEV=8
MEHIS=8
MIS=0
ADULT=18
NCRIME=7
NOC=4
PRG=0.
NSBOX=8
NEBOX=0
NCHARG=7
ISEED=60617
ICCC=1000
MICCC=200
TSTOP=50
TINITL=0
MBEGIN=0
NDISP=1
NSDISP=1
RTIME=1.
DO 11 IG=1,MRES
11 RGROW(IG)=0.
    SINITQ=0.
    READ(8,PARAM)
    IF(MEQUE.LE.0) SINITQ=0
    TINITL=AMAX1(0.,TINITL)
    TINITL=AMIN1(TSTOP,TINITL)
    RTIME=AMIN1(RTIME,(TSTOP-TINITL))
    RTIME=(RTIME+TINITL)*360.
    DCCC=ICCC
    IF(MERES.LE.0) PRG=8.
    DO 18 IG=1,MRES
18 RGROW(IG)=RGROW(IG)/12.
C
C   PERFORM ERROR CHECKS
MENTRU=(TSTOP*360+FSHOT)/TCALL+1
IF(MCELL-MENTRU) 10,50,50
10 TSTOP=((MCELL-1)*TCALL+FSHOT)/360.
WRITE(6,7) TSTOP
7  FORMAT(1H0,*USER INPUT WARNING:  TSTOP .NE. MCELL*,
* 10X,*NEW TSTOP =*,F10.2)
IF(TSTOP.LE.TINITL) STOP
50 INDLST=IP24+ISP12
IF(MAXIA-INDLST) 8,51,51
8  WRITE(6,9) MAXIA,INDLST
9  FORMAT(1H0,*USER INPUT ERROR:  MAXIA =*,I7,* .GT. ACTUAL =*,5I7)
STOP
C
C   NP(I=1,NPN)   ARE POINTERS TO SUBARRAYS OF UDATA
51 NPN=32
IND=NPN
C
C   READ OFFENDER DATA
NCODE=8

```

```

      IF(DUMP)WRITE(6,2)
2  FORMAT(* FOLLOWING ARE THE NAMES AND INDICES*,
* * OF USER INPUT ARRAYS CONTAINING PROBABILITIES */)
3  FORMAT(10X,I4,*, NAME:  *,A10,*,      INDICES:*,
* 10X,A10,*=*,I5,10X,A10,*=*,I5)
      DO 12 N=1,NOC
      READ(8,OFFENDR)
      DO 12 IK=1,NCRIME
      DEMO(IK,N,1)=CAT
      DEMO(IK,N,2)=PPOP(IK)
      DEMO(IK,N,5)=AMIN(IK)
      DEMO(IK,N,6)=AMAX(IK)
C      CONVERT MEAN AND STD. DEV. TO PARAMETERS OF GAMMA DISTN.
      DEMO(IK,N,4)=ASD(IK)*ASD(IK)
      DEMO(IK,N,3)=ABAR(IK)/DEMO(IK,N,4)
      DEMO(IK,N,4)=ABAR(IK)*DEMO(IK,N,3)
      IF(DEMO(IK,N,4).GT.100.) DEMO(IK,N,4)=1.
12  CONTINUE
C
C      STORE OFFENDER DATA
      NP(12)=IND+1
      NARRAY=10HDEMO(2)
      NIND1=10HCRIME
      DO 306 IK=1,NCRIME
      NCODE=NCODE+1
      IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,IK
      DO 306 N=1,NOC
      DO 306 J=1,6
      IND=IND+1
C      STORE CUMULATIVE PROBABILITIES
      IF(J.NE.2)GO TO 306
      IF(N.GT.1)DEMO(IK,N,J)=DEMO(IK,N,J)+DEMO(IK,N-1,J)
      IF(N.EQ.NOC.AND.DEMO(IK,NOC,2).LT..9999999)GO TO 400
      IF(DEMO(IK,N,J).GT.1.05)GO TO 400
306  UDATA(IND)=DEMO(IK,N,J)
C
C      STORE SERVICE TIMES IN UDATA (STIME SUBARRAY)
      NP(3)=IND+1
      DO 100 I=1,NSBOX
C      READ SERVICE TIMES--EACH ARRAY MUST HAVE 7 VALUES
      READ(8,STIME)
      DUM(I,1)=ID
      DO 100 J=1,NCRIME
      IND=IND+1
100  UDATA(IND)=TBAR(J)
C
C      CREATE POINTERS FOR SUBARRAY STIME AND STORE IN IPST
      NP(1)=IND+1
      DO 97 ID=1,MBOX
      DUM(ID,2)=0
      DO 98 J=1,NSBOX
98  IF(DUM(J,1).EQ.ID)DUM(ID,2)=NP(3)+(J-1)*NCRIME
      IND=IND+1
97  UDATA(IND)=DUM(ID,2)

```

```

C
C   STORE ARC TRANSITION PROBABILITIES
NP(4)=IND+1
NARRAY=10HARC
NIND1=10HARC SOURCE
NIND2=10HARC SINK
DO 200 I=1,NEBOX
C   READ AND STORE MATRIX; EACH SOURCE NODE MUST
C   HAVE 7 CRIME ENTRIES PER ARC
READ(8,FLOUT)
DUM(I,1)=ID
IF(NARC.GT.MAXARC)GO TO 403
IF(ID.EQ.23)GO TO 13
IF(ID.EQ.38)GO TO 14
IF(ID.EQ.32)GO TO 15
GO TO 17
13 IF(IDARCS(1).NE.25)GO TO 404
IF(IDARCS(2).NE.28)GO TO 404
IF(IDARCS(3).NE.54)GO TO 404
GO TO 16
14 IF(IDARCS(1).NE.31)GO TO 405
IF(IDARCS(2).NE.32)GO TO 405
GO TO 16
15 IF(IDARCS(1).NE.37)GO TO 406
IF(IDARCS(2).NE.39)GO TO 406
16 DO 130 J=1,NARC
NCODE=NCODE+1
IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,ID,NIND2,IDARCS(J)
DO 130 K1=1,MCRIME
IND=IND+1
C   TEST CUMULATIVE PROBABILITIES
IF(J.GT.1)GO TO 128
TARC(K1)=ARC(K1,J)
GO TO 129
128 TARC(K1)=TARC(K1)+ARC(K1,J)
129 IF(TARC(K1).GT. 1.05)GO TO 408
IF(J.EQ.NARC.AND.TARC(K1).LT..9999999)GO TO 408
UDATA(IND)=ARC(K1,J)
130 IF(J.EQ.1.AND.K1.EQ.1) DUM(I,2)=IND
GO TO 200
17 CALL LOCF(ID,1,LOCP,LOCPP)
DO 140 J=1,NARC
IF(IDARCS(J).NE.IA(LOCP))GO TO 401
LOCP=LOCP+1
NCODE=NCODE+1
IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,ID,NIND2,IDARCS(J)
DO 140 K1=1,MCRIME
IND=IND+1
C   STORE CUMULATIVE PROBABILITIES
IF(J.GT.1)ARC(K1,J)=ARC(K1,J)+ARC(K1,J-1)
IF(ARC(K1,J).GT.1.05)GO TO 400
IF(J.EQ.NARC.AND.ARC(K1,J).LT..9999999)GOTO 400
UDATA(IND)=ARC(K1,J)
140 IF(J.EQ.1.AND.K1.EQ.1) DUM(I,2)=IND
200 CONTINUE

```

```

C
C   CREATE POINTERS TO ARC AND STORE IN SUBARRAY IPARC
NP(2)=IND+1
DO 201 IO=1,MBOX
IND=IND+1
IUDATA(IND)=0
DO 201 J=1,NEBOX
201 IF(DUM(J,1).EQ.IO)IUDATA(IND)=DUM(J,2)
C
C   READ CRIME SEVERITY & SWITCH MATRICES & PRE-TRIAL DETENTION PROB.
DO 202 I=1,NCRIME
202 SEVERE(I)=1.0
TSEVER=0.
READ(8,CRIMES)
C
C   STORE CRIME SWITCH MATRIX
NP(5)=IND+1
IO=0
NARRAY=10H SWITCH
NIND1=10H ORIG CRIME
DO 220 I=1,NCRIME
NCODE=NCODE+1
IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,I
DO 220 J=1,NCRIME
IND=IND+1
C   STORE CUMULATIVE PROBABILITIES
IF(J.GT.1)SWITCH(J,I)=SWITCH(J,I)+SWITCH(J-1,I)
IF(SWITCH(J,I).GT.1.05)GOTO 400
IF(J.EQ.NCRIME.AND.SWITCH(J,I).LT..99999999)GOTO 400
220 UDATA(IND)=SWITCH(J,I)
C
C   COMPUTE AVERAGE CRIME SEVERITY TO BE USED IN THE PROCESSING OF
C   INFORMATION ON THE CURRENT OFFENSE OF THE DEFENDANT
ACS=0
DO 221 I=1,NCRIME
221 ACS=ACS+SEVERE(I)
ACS=ACS/FLOAT(NCRIME)
IF(TSEVER.GT.0.)ACS=TSEVER
C
C   STORE CRIME SEVERITIES
NP(14)=IND+1
DO 300 I=1,NCRIME
IND=IND+1
300 UDATA(IND)=SEVERE(I)
C
C   READ(8,PLEA)
C
C   STORE PLEA BARGAINING TRANSITION MATRIX
NP(6)=IND+1
NARRAY=10H BARGAN
NIND1=10H ARREST CHG
DO 300 I=1,NCRIME
NCODE=NCODE+1
IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,I

```

```

      DO 300 J=1,NCHARG
      IND=IND+1
C     STORE CUMULATIVE PROBABILITIES
      IF(J.GT.1)BARGAN(I,J)=BARGAN(I,J)+BARGAN(I,J-1)
      IF(J.EQ.NCHARG.AND.BARGAN(I,J).LT..9999999)GO TO 400
      IF(BARGAN(I,J).GT.1.05)GO TO 400
300  UDATA(IND)=BARGAN(I,J)
C
C     STORE PLEA DISPOSITION MATRIX
      NP(8)=IND+1
      NARRAY=10HPDISP
      NIND1=10HPLEA CHARG
      DO 302 I=1,NCHARG
      NCODE=NCODE+1
      IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,I
      DO 302 J=1,NDISP
      IND=IND+1
C     STORE CUMULATIVE PROBABILITIES
      IF(J.GT.1)PDISP(I,J)=PDISP(I,J)+PDISP(I,J-1)
      IF(PDISP(I,J).GT.1.05)GO TO 400
      IF(J.EQ.NDISP.AND.PDISP(I,J).LT..9999999)GOTO 400
302  UDATA(IND)=PDISP(I,J)
C
C     STORE PLEA BARGAINED SENTENCE DURATION
      NP(10)=IND+1
      DO 304 I=1,NCHARG
      DO 304 J=1,NSDISP
      IND=IND+1
304  UDATA(IND)=PSDUR(I,J)
C
C     READ(8,COURT)
C
C     STORE SUPERIOR COURT CONVICTION MATRIX
      NP(7)=IND+1
      NARRAY=10HCONVIC
      NIND1=10HARREST CHG
      DO 301 I=1,NCRIME
      NCODE=NCODE+1
      IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,I
      DO 301 J=1,NCHARG
      IND=IND+1
C     STORE CUMULATIVE PROBABILITIES
      IF(J.GT.1)CONVIC(I,J)=CONVIC(I,J)+CONVIC(I,J-1)
      IF(CONVIC(I,J).GT.1.85)GO TO 400
      IF(J.EQ.NCHARG.AND.CONVIC(I,J).LT..9999999)GOTO 400
301  UDATA(IND)=CONVIC(I,J)
C
C     STORE SUPERIOR COURT TRIAL DISPOSITION MATRIX
      NP(9)=IND+1
      NARRAY=10HTDISP
      NIND1=10HCONV CHARG
      DO 303 I=1,NCHARG
      NCODE=NCODE+1
      IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,I
      DO 303 J=1,NDISP

```



```

      IND=IND+1
C     STORE CUMULATIVE PROBABILITIES
      IF(J.GT.1)TDISP(I,J)=TDISP(I,J)+TDISP(I,J-1)
      IF(TDISP(I,J).GT.1.05)GO TO 400
      IF(J.EQ.NDISP.AND.TDISP(I,J).LT..9999999)GO TO 400
303  UDATA(IND)=TDISP(I,J)
C
C
C     STORE TRIAL SENTENCE DURATION
      NP(11)=IND+1
      DO 305 I=1,NCHARG
      DO 305 J=1,NSDISP
      IND=IND+1
305  UDATA(IND)=TSDUR(I,J)
C
      READ(8,LCOURT)
C
C     STORE LOWER COURT SENTENCE PROBABILITES
      NP(13)=IND+1
      NARRAY=10HDISPL
      NIND1=10HCRIME
      DO 307 I=1,NCRIME
      NCODE=NCODE+1
      IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,I
      DO 307 J=1,NDISP
      IND=IND+1
C     STORE CUMULATIVE PROBABILITIES
      IF(J.GT.1)DISPL(I,J)=DISPL(I,J)+DISPL(I,J-1)
      IF(DISP(I,J).GT.1.05)GOTO 400
      IF(J.EQ.NDISP.AND.DISP(I,J).LT..9999999)GOTO 400
307  UDATA(IND)=DISPL(I,J)
C
C     STORE LOWER COURT SENTENCE DURATIONS
      IJK=IND+1
      DO 313 I=1,NCRIME
      DO 313 J=1,NSDISP
      IND=IND+1
313  UDATA(IND)=SDURL(I,J)
      IND=IND+1
      IUATA(IND)=IJK
C
C     STORE PRE-TRAIL DETENTION PROBABILITEIS: JUVENILE & ADULT
      NP(15)=IND+1
      JND=IND
      NARRAY=10HA/Y JAIL
      NIND1=10HCRIME
      DO 309 I=1,NCRIME
      JND=JND+1
      NCODE=NCODE+1
      IF(DUMP)WRITE(6,3)NCODE,NARRAY,NIND1,I
      IF(YJAIL(I).GT.1.05.OR.AJAIL(I).GT.1.05)GO TO 400
      UDATA(JND)=YJAIL(I)
      KND=JND+NCRIME
      UDATA(KND)=AJAIL(I)

```

```

      IND=KND+NCRIME
309 UDATA(IND)=CJAIL(I)
C
C   READ PAROLE DATA
      DO 310 I=1,NCHARG
        PRISONH(I)=1.
        PRISONF(I)=1.
310 PVIOL(I)=0.
      READ(8,PAROLE)
C
C   STORE PAROLE DATA
      NP(16)=IND+1
      DO 311 I=1,NCHARG
        IND=IND+1
311 UDATA(IND)=PRISONH(I)
      DO 312 I=1,NCHARG
        IND=IND+1
312 UDATA(IND)=PRISONF(I)
      NP(17)=IND+1
      DO 317 I=1,NCHARG
        IND=IND+1
317 UDATA(IND)=DPAROL(I)
      DO 318 I=1,NCHARG
        IND=IND+1
318 UDATA(IND)=PVIOL(I)
C
C   READ RECIDIVISM DATA
      DO 319 I=1,7
        PROBM(I)=0.
319 PROBF(I)=0.
      READ(8,RECID)
C
C   STORE RECIDIVISM PROBABILITIES
      NP(18)=IND+1
      DO 314 I=1,7
        IND=IND+1
        IN1=IND+7
        UDATA(IND)=PROBF(I)
314 UDATA(IN1)=PROBM(I)
      IND=IN1
C
C   STORE RECIDIVISM DELAY TIMES
      NP(19)=IND+1
      DO 315 I=1,7
        IND=IND+1
        IN1=IND+7
        IN2=IN1+7
        IN3=IN2+7
        IN4=IN3+7
        UDATA(IND)=DELPRO(I)
        UDATA(IN1)=DELFI(I)
        UDATA(IN2)=DELDIS(I)
        UDATA(IN3)=DELPAR(I)
315 UDATA(IN4)=DELPRI(I)
      IND=IN4

```

```

C
C   CREATE POINTERS FOR USER STATISTICS
NP(20)=IND+1
NP(21)=NP(20)+NOC+1
NP(22)=NP(21)+NOC*20+1
NP(23)=NP(22)+NOC*NCRIME+1
NP(24)=NP(23)+NOC*12+1
NP(25)=NP(24)+NOC*8+1
NP(26)=NP(25)+NOC*MICCC+1
MONTHS=IFIX(TSTOP*12.)+IFIX(TINITL*12.)
IYEARS=MONTHS/6
NP(27)=NP(26)+NOC*IYEARS
NP(28)=NP(27)+NOC*IYEARS
NP(29)=NP(28)+NOC*IYEARS
NP(30)=NP(29)+NOC*IYEARS
NP(31)=NP(30)+NOC*20+1
NP(32)=NP(31)+NOC*20+1

C
C   INITIALIZE STATISTICS COLLECTION ARRAYS
IN1=NP(20)
IN2=NP(26)-1
DO 316 IND=IN1,IN2
316 IUDATA(IND)=0
   IB=NP(20)
   IUDATA(IB)=NOC
   IB=NP(21)
   IUDATA(IB)=20
   IB=NP(22)
   IUDATA(IB)=NCRIME
   IB=NP(23)
   IUDATA(IB)=12
   IB=NP(24)
   IUDATA(IB)=8
   IB=NP(25)
   IUDATA(IB)=MICCC
   IN1=NP(30)
   IN2=NP(32)-1
   DO 320 IND=IN1,IN2
320 IUDATA(IND)=0
   IB=NP(30)
   IUDATA(IB)=20
   IB=NP(31)
   IUDATA(IB)=20

C
C   INITIALIZE TIME SERIES COLLECTION ARRAYS
IN1=NP(26)
IN2=NP(30)-1
DO 321 IND=IN1,IN2
321 UDATA(IND)=0.
   DO 3211 IND=1,NOC
   SCC(IND)=0.
   SNOFS(IND)=0.
   ICOF(IND)=0
3211 SAGE(IND)=0.

```

```

C      DO 322 ICRIME=1,NCRIME
C      DO 322 IB=1,NOC
C      ANOFS(IB,ICRIME)=0.
322 NO(IB,ICRIME)=0
C      DO 323 I=1,MRES
C      RSUM(I)=0
C      RSQ(I)=0
C      RMAX(I)=0
323 RNUM=0
C
C      CHECK THE SIZE OF THE USER ARRAY
C      IF(NP(NPN).GT.MAXUD) GOTO 402
C
C      IF(DUMP) WRITE(6,5)
5  FORMAT(1H0,10X,*THERE ARE NOT ANY OBVIOUS ERRORS IN THESE*,
C      *  * PROBABILITIES*)
C
C      ECHO CHECK THE USER DATA
C      CALL USERD(D1,D2,D3,D4,D5,D6,D7,D8,D9,MRES,LOCRES,IFREQ,
C      *  ATRIB,IATRIB,TS)
C      DUMP=.FALSE.
C      RETURN
C
C      #####
C      ERRORS OCCURRED IN USER INPUT DATA
C      #####
C
C      *10H NE 1 IN: ,NARRAY),RETURNS(500,500)
C      GO TO 500
401 CALL ERRIN(ID,IDARCS(J),SUBN,10HINCORRECT ,10HORDERING 0,
C      *10HF ARCS FOL,10HLOWING BOX),RETURNS(500,500)
C      GO TO 500
402 WRITE(6,4) NP(NPN), MAXUD
4  FORMAT(1H0,* SIZE REQUIRED FOR USER ARRAY:*,I6,
C      *  * SIZE ALLOCATED:*,I6)
C      CALL ERRIN(0,47,SUBN,10HINSUFF STO,10HRAGE IN UD,
C      *10HATA: CHECK,10H MAXUD:      ),RETURNS(500,500)
C      GO TO 500
403 WRITE(6, 6) ID,NARC,MAXARC
6  FORMAT(* ERROR IN USERB: # OF FOLLOWER BOXES OF BOX*,
C      *I4,* IS MISSPECIFIED*, 2I10)
C      GO TO 500
404 CALL ERRIN(ID,ID,SUBN,10HFOR BOX 23,10H: IDARCS ,
C      *10HMUST BE 25,10H, 28, 54  ),RETURNS(500,500)
C      GO TO 500
405 CALL ERRIN(ID,ID,SUBN,10HFOR BOX 30,10H: IDARCS ,
C      *10HMUST BE 31,10H, 32      ),RETURNS(500,500)
C      GO TO 500
406 CALL ERRIN(ID,ID,SUBN,10HFOR BOX 32,10H: IDARCS ,
C      *10HMUST BE 37,10H, 39      ),RETURNS(500,500)
500 DUMP=.TRUE.
C      IERROR=IERROR+1
9000 RETURN
C      END

```

```

C*****
C
      SUBROUTINE USERC(ID,IADR,N,VAL,NN,D1,D2,D3,D4,D5,D6,D7,D8,D9,
      *NRES,LOCRES,IFREQ,ATRI,ITRIB,TS), RETURNS(MQXI,MXYZ)
C
C      PURPOSE:  TO EXECUTE SPECIAL USER-SUPPLIED LOGIC
C                DURING SIMULATION OF MODEL.
C*****
C
      COMMON/BASE/ARRAY(50000),UDATA(3000)
      COMMON/CJS/MCRIME,CRIME,NCHARG,NOISP,NSDISP,DUMP,NPN,ADULT,
      * NOC,MBEGIN,ACS,PRG,MEQUE,MERES,MESEV,MEHIS,MIS,MONTHS,IYEARS,
      * DCCC,MICCC,SCCC,SNOFS,ICOF,TSTOP,TINITL,IERROR,ANO,TRACEF,
      * ANDFS(4,7),NO(4,7),RSUM(10),RSQ(10),RMAX(10),RNUM,RTIME,SAGE
      * ,RGROW(10),SINITQ
      COMMON/GLOBAL/C1,C2,C3,FSHOT,IR,IP,IGO,IFROM,ITS1,IFR1,IAVAIL,
      * IDRUN, ITO, IRATE, ISTUP, IPRTY, ISPSEG, IFULL, ISP1, ISP8, ISP9,
      * ISP10, ISP11, ISP12, ISP15, ISP21, IP1, IP2, IP3, IP4, IP5, IP6,
      * IP7, IP8, IP9, IP10, IP11,ISEED, ITOP,IP15F, IP15, IP16, IP17,
      * IP18, IP19, IP20, IP21, IP22, IP23, IP24, JHALF, K, LOCR2,
      * MAXAR, MAXUD, MAXIA, MAXID, MHST, MENTRY, MRES, MBOX,MRES1,
      * MMRES, MDELET, MWORK, MV, MCELL, NQBOX,NFYAR,NST,
      * MERR, NOWPAS, MPASS, NBOX, NGRP, NETRL, NTRACE, NCALL, NSINK,
      * NQB1, NQB2, NSOUR, NDBOX, NRBOX, NATRIB, NCELL,TCALL,UTIME,
      * ISW1, ISW2, ISW3, ISW4, ISW5, VAR1, VAR2, VAR3, VAR4, VAR5, LINE,
      * NRATE, IWRITE, IPASS, KSUM, LTOP, TNOW, TLAST,
      * NOOMP, CONT, COST, END, NXTMOD,QUE, RESC, RESCHG, SEPR,
      * STDEP, TMCOST, UIN, UOUT, UFORM, STCHG, NOPREM, LU1, LU2, LU3, LU4,
      * LU5, LU6, LU7, LU8, LU9, LU10,LLAG, LLSEGM, LORS
C
      LOGICAL LU1, LU2, LU3, LU4, LU5, LU6, LU7, LU8, LU9, LU10, LLAG,
      * LLSEGM, LORS
      LOGICAL CONT, COST, END, NXTMOD,QUE, RESC, RESCHG, SEPR,
      * STDEP, TMCOST, UIN, UOUT, UFORM, STCHG, NOPREM, NOOMP
      LOGICAL TRACEC, TRACED, TRACEF, TRACEQ, TRACER
C
      INTEGER D1,D2,D3,D4,D5,D6,D7,D8,D9,SUBN,RACEX,IARREST(7),
      * RARREST(7), CRIME(7), NP(100)
      INTEGER IA(50000),LOC(100),NRES(D1,D4),LOCRES(D4,D5),
      * IFREQ(D8,D9),IUDATA(3000),IARRAY(50000),IATRIB(D2,D3)
C
      REAL A(5),A1(5),A3(5),TS(D6,D7),ATRIB(D2,D3),
      * MHORT(17),PI(3),FMORT(17),NORM1(4),AND(7),ICOF(4),SCCC(4),
      * SNOFS(4),SAGE(4),RESLV(10),RES(10)
C
      EQUIVALENCE (ARRAY(1),IARRAY(1),IA(1),LOC(1)),
      * (UDATA(1), IUDATA(1), NP(1))
C
      DATA A1/0.,0.,9999.,1.,0./
      DATA A3/0.,0.,0.,1.,0./
      DATA NORM1/0.,-2.,2.,.75/
      DATA SUBN/8HUSERC /
      DATA IARREST, RARREST/14*0/

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DATA PROBM1, PROBM2/ 1., 1./
DATA JSEED/1111111/
DATA ICOFS/0/
DATA MONTH1/0/
DATA MULT/10/
DATA LADR/0/
DATA IERRS/0/
DATA RR/1./
DATA TRACEC,TRACED,TRACEQ,TRACER/ .FALSE...FALSE...TRUE...TRUE./
DATA MMORT/57.8,57.8,57.8,53.0,48.3,43.9,39.6,35.2,31.0,26.8,23.,
*      19.4,16.3,13.5,10.9,9.7,7.5/
DATA FMORT/65.6,65.6,65.6,60.7,55.8,51.1,46.4,41.7,37.2,32.7,
*      28.5,24.5,20.7,17.2,13.8,11.3,8.9/

C
C  GNS INLINE FUNCTIONS:
MSERV(I)=IA(LOC(31)+I-1)
KRATE(I)=IA(LOC(19)+I-1)
LC(I,J)=LOC(I)+J-1
MAXLV(I)=IA(LOC(24)+I-1)
NOWLV(I)=IA(LOC(25)+I-1)
LOGLS(I)=IA(LC(6,I))
LOGDS(I)=IA(LC(5,I))
NEXT(I)=IA(LC(39,I))
INITQ(I)=IA(LC(28,I))
KOSTR(I)=IA(LOC(26)+I-1)
NWAIT(I)=IA(LC(34,I))
IDLE(I)=IA(LC(32,I))
LIST(I)=IA(LC(40,I))

C
C  INLINE FUNCTIONS TO DECODE USER INPUT DATA
ISTAT(I,J,K)=IUDATA( NP(19+I) + J + (K-1)*IUDATA(NP(19+I)) )
SEVERE(I)=UDATA(NP(14)+I-1)
DEMO(K,I,J)=UDATA(NP(12)+6*(I-1)+(J-1)+NOC*6*(K-1))
AJAIL(I)=UDATA(NP(15)+NCRIME+I-1)
CJAIL(I)=UDATA(NP(15)+2*NCRIME+I-1)
YJAIL(I)=UDATA(NP(15)+I-1)
IPST(I,J)=IUDATA(NP(1)+I-1)+J-1
PAROLE(I,J)=UDATA(NP(15+J)+I-1)
RECID(IDEL,IAGE,IRS)=UDATA(NP(18+IDEL)+7*(IRS-1)+IAGE)
TDISP(I,J)=UDATA(NP(9)+(I-1)*NDISP+J-1)
PDISP(I,J)=UDATA(NP(8)+(I-1)*NDISP+J-1)
CONVIC(I,J)=UDATA(NP(7)+(I-1)*NCHARG+J-1)
BARGAN(I,J)=UDATA(NP(6)+(I-1)*NCHARG+J-1)
SWITCH(I,J)=UDATA(NP(5)+(I-1)*NCRIME+J-1)
TSDUR(I,J)=UDATA(NP(11)+(I-1)*NSDISP+J-1)
PSDUR(I,J)=UDATA(NP(10)+(I-1)*NSDISP+J-1)
IPARC(I)=IUDATA(NP(2)+I-1)
DISPL(I,J)=UDATA(NP(13)+(I-1)*NSDISP+J-1)
SDURL(I,J)=UDATA(IUDATA(NP(15)-1)+(I-1)*NSDISP+J-1)

C
C  INLINE FUNCTIONS TO DECODE OFFENDER ATTRIBUTES
FAGE(IADR)=AMOD(ATRIB(IADR,3),1000.)
FRACEX(IADR)=AMOD(ATRIB(IADR,3),10000.)/1000.+5
FSEX(IADR)=AMOD(FRACEX(IADR),2.)
FCRIME(IADR)=AMOD(ATRIB(IADR,3),100000.)/10000.+5
FDEATH(IADR)=IFIX(ATRIB(IADR,3)/100000.)/10.

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C
C
C      GO TO (8001, 2000, 8001, 4000, 1100, 1000, 8001), N
C
C
C      #####
C      ERROR OCCURRED WITH USER INPUT DATA:  TERMINATE RUN
C      #####
C
1000 IF(IERROR.GT.0) GO TO 1002
      IASIZE=ISP12+IP24
      IF(MAXIA.LT.IASIZE) GO TO 1001
C
      WRITE(6,12) NOWPAS
12  FORMAT(1H1,4DX,*TRACE THE EXECUTION OF RUN*,I7/1H0)
      DINITL=TINITL*360.
      DO 1003 IG=1,MRES
      RGROW(IG)=RGROW(IG)+1.
1003 RESLV(IG)=MAXLV(IG)
      GO TO 1110
C
1001 WRITE(6,16) MAXIA
      16 FORMAT(1H0,*GNS ERROR:  ARRAY CAPACITY*,I7,*  EXCEEDED*)
1002 ITO=5
      GO TO 9002
C
C      #####
C      END CONTROL BOX 1:  CREATE VIRGIN ARRESTEES USING TIME SERIES FORCA
C      #####
C
1100 IF(ID.NE.1)GO TO 5000
C
1110 MONTH=TNOW/30.+1.05
C
C      INCREASE THE PROSECUTOR'S RESOURCES, AND COST FOR MIS
      IF(MONTH.NE.MBEGIN)GO TO 60
      IF(MERES.LE.0)GO TO 50
      PP=1.
      IF(MERES.NE.3) PP=2.
      RR=1.+(PRG/PP)
      RESLV(1)=RESLV(1)*(1.+PRG)
50  IB=LOC(26)
      IF(MEHIS.GT.0) IA(IB)=KOSTR(1)+MIS
C
C      FOR INITIALIZATION PERIOD, RESET FORECAST TIME TO MONTH=1
C      AND DETERMINE PRE-TRIAL QUEUE LENGTH FOR PROSECUTORIAL DECISIONS
60  IF(TNOW-DINITL) 61,61,62
61  MONTH1=MONTH-1
62  MONTH=MONTH-MONTH1
C
C      FORECAST NUMBER OF OFFENDERS; INSERT INTO IN-PROGRESS LIST OF BOX 2
C      SET ARREST DATE
      IF(TRACEF) WRITE(6,11) TNOW
11  FORMAT(1H0,*AT TIME*,F10.2)

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DO 106 ICRIME=1, NCRIME
NOF=FORCAST(MONTH, ICRIME)
IF (NOF.LT.1) GO TO 105
IF (TNOW.GE.DINITL) IARREST(ICRIME)=IARREST(ICRIME)+NOF
DATE=TNOW
DDATE=29.95/FLOAT(NOF)
DO 108 IK=1, NOF
DATE=DATE+DDATE
IADR=0
CALL ENTER(-2,1,IADR,JADR,DATE,02,03,ATRIB), RETURNS(9000)
IB=LOC(40)+IADR-1
IA(IB)=2
C
C   DETERMINE OFFENDER'S DEMOGRAPHIC VARIABLES (RACE, SEX)
B=Rand(JSEED)
DO 70 RACEX=1, NOC
70 IF (B.LE.DEMO(ICRIME, RACEX, 2)) GO TO 71
RACEX=NOC
C
C   DETERMINE OFFENDER'S AGE
71 A(2)=DEMO(ICRIME, RACEX, 5)
A(3)=DEMO(ICRIME, RACEX, 6)
A(4)=DEMO(ICRIME, RACEX, 4)
A(5)=DEMO(ICRIME, RACEX, 3)
CALL GAMMA(JSEED, AGE, A)
IAGE=AGE/5.+1.
IB=NP(30)+IAGE+(RACEX-1)*IUDATA(NP(30))
IUDATA(IB)=ISTAT(11, IAGE, RACEX)+1
C
C   DETERMINE OFFENDER'S AGE AT DEATH
ADD=HMORT(IAGE)
IF (MOD(RACEX, 2).EQ.0) ADD=FMORT(IAGE)
A3(3)=DEMO(ICRIME, RACEX, 6)-AGE
A3(5)=ADD
CALL ERLNG(ISEED, ADD, A3)
DAGE=AGE+ADD
C
C   SAVE OFFENDER'S CHARACTERISTICS
ICOD1=RACEX*1000.
ICOD2=ICRIME*10000.
ICOD3=IFIX(DAGE*10.)*100000.
ATRIB(IADR, 3)=AGE+ICOD1+ICOD2+ICOD3
C
C   INITIALIZE SCRATCH ATTRIBUTE
ATRIB(IADR, 4)=0.
C
C   INITIALIZE CAREER CRIMINAL COST
ATRIB(IADR, 5)=0.
C
C   INITIALIZE NUMBER OF ARRESTS
ATRIB(IADR, 6)=1+100*ICRIME
C
C   ARRAY OVERFLOW, TERMINATE SIMULATION
IF (MENTRY-IADR=25) 90, 100, 100
90 TSTOP=TNOW/360.+0.001

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TINITL=AMIN1(TSTOP,TINITL)
DINITL=TINITL*360.
MCELL=AMIN1((TSTOP*4.+1), FLOAT(MCELL))
WRITE(6,15) TNOW,IADR
15 FORMAT(1H0,*AT TIME*,F10.2,15X,* ARRAY OVERFLOW IS EXPECTED*,
*      * WITH NEW OFFENDER AT ADDRESS*, I5)
IERRS=IERRS+1
GO TO 110
C
100 CONTINUE
C
IF(TRACEF) WRITE(6,2) MONTH,ICRIME,NOF,IADR
2 FORMAT(* AT MONTH *,I7,6X,* THE CRIME*,I2,* FORECAST IS*,
*I10,4X,* WHILE THE ADDRESS OF THE LAST OFFENDER IS*,I5)
C
105 CONTINUE
106 CONTINUE
C
LADR=AMAX0(LADR,IADR)
C
C COLLECT TIME SERIES OF AVERAGE CAREER CRIMINAL COST, AVERAGE
C NUMBER OF OFFENSES PER OFFENDER, AVERAGE RATIO OF THESE SERIES, AND
C AVERAGE AGE AT DESISTANCE (AVERAGES COMPUTED OVER HALF-YEAR PERIOD)
110 IF(N.EQ.6) GO TO 9001
IF(MONTH.LE.1) GO TO 160
IF(MOD((MONTH-1),6).NE.0) GO TO 160
IYEAR=(MONTH-1)/6.+1.
IF(IYEAR.GT.IYEARS) GO TO 160
DO 155 IOF=1,NOC
I=NP(26)+IYEAR+(IOF-1)*IYEARS
J=NP(27)+IYEAR+(IOF-1)*IYEARS
IJ=NP(28)+IYEAR+(IOF-1)*IYEARS
IJ1=NP(29)+IYEAR+(IOF-1)*IYEARS
IF(ICOF(IOF).EQ.0) GO TO 149
B=ICOF(IOF)
UDATA(I)=SCCC(IOF)/B
UDATA(J)=SNOFS(IOF)/B
UDATA(IJ)=SCCC(IOF)/SNOFS(IOF)
UDATA(IJ1)=SAGE(IOF)/B
GO TO 150
149 UDATA(I)=0.
UDATA(J)=0.
UDATA(IJ)=0.
UDATA(IJ1)=0.
150 SAGE(IOF)=0.
ICOF(IOF)=0.
SNOFS(IOF)=0.
155 SCCC(IOF)=0.
C
C COLLECT STATISTICS ON RESOURCE USAGE BETWEEN DINITL AND RTIME
160 IF(MONTH.LE.1) GO TO 200
IF(TNOW.GT.RTIME) GO TO 180
DO 170 IK=1,MRES
RES(IK)=MAXLV(IK)*NOWLV(IK)
RSUM(IK)=RSUM(IK)+RES(IK)

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      RSQ(IK)=RSQ(IK)+RES(IK)**2
170 RMAX(IK)=AMAX1(RMAX(IK),RES(IK))
      RNUM=RNUM+1
      IF(TRACER) WRITE(6,27) MONTH,(RES(IK),IK=1,MRES)
27  FORMAT(1H0,*AT MONTH *,I7,6X,*RESOURCE USAGE:*,6X,10F8.0)
      IF(.NOT.TRACEQ) GO TO 180
      IQTRIAL=NWAIT(37)+NWAIT(39)
      WRITE(6,29) MONTH,IQTRIAL
29  FORMAT(* AT MONTH *,I7,6X,* PRE,TRIAL QUEUE:*,5X,I7,*,*)
C
C      UPDATE MAX. LEVEL OF RESOURCES BASED UPON MONTHLY GROWTH RATES
180 DO 181 IG=1,MRES
      RESLV(IG)=RESLV(IG)*RGROW(IG)
      RG=RESLV(IG)/MAXLV(IG)
      IB=LOC(24)+IG-1
      IA(IB)=MAXLV(IG)+RG
      IB=LOC(25)+IG-1
181 IA(IB)=NOWLV(IG)+RG
      IF(.NOT. TRACER) GO TO 200
      IB1=LOC(24)
      IB2=LOC(24)+MRES-1
      WRITE(6,28) MONTH,(IA(IB),IB=IB1,IB2)
28  FORMAT(* AT MONTH *,I7,6X,*MAX. RESOURCE LEVELS:*,10(I7,*,*))
C
C      RELEASE BOX 1 & RETURN
200 NN=1
      RETURN
C
C      #####
C      FOR OFFENDER WHO IS JAILED BEFORE TRIAL, SAVE TIME DETENTION BEGINS
C      #####
C
2000 IF(ID.EQ.10) GO TO 2001
      IF(ID.EQ.22) GO TO 2001
      GO TO 8000
C
2001 VAL=9999.
      ATRIB(IADR,4)=ATRIB(IADR,1)
      RETURN
C
C      #####
C      START CONTROL LOGIC
C      #####
C
4000 ICRIME=FCRIME(IADR)
      AGE=FAGE(IADR)
C
      GO TO (8000,8000,4900,4021,4001,8000,4900,4001,4001,8000,
*      8000,4001,4001,4001,4001,8000,8000,4900,4500,4600,
*      4001,8000,4001,8000,4001,4105,4900,4001,8000,8000,
*      8000,8000,8000,4900,4900,4900,8000,8000,4001,4104,
*      4104,4105,8000,8000,4120,4900,4500,4500,4600,8000,
*      4105,8000,8000,8000,8000,8000,8000,8000), ID

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C
C   DETERMINE SERVICE TIMES:
4001 A1(5)=UDATA(IPST(ID,ICRIME))
      CALL ERLNG(ISEED,ST,A1), RETURNS(9000)
C
C   CHANGE SERVICE TIME IF OFFENDER DIES, SAVE ST
4010 TAGE1=ST/360.
      TAGE=AGE+TAGE1
      DAGE=FDEATH(IADR)
      IF(TAGE.LT.DAGE) GO TO 4011
      ST=.05*ST
      IF(DAGE.GT.AGE) ST=(DAGE-AGE)*360.
      TAGE1=ST/360.
      ATRIB(IADR,3)=AMOD(ATRIB(IADR,3),100000.)
4011 ATRIB(IADR,1)=TNOW+ST
      CALL SORT(6,ATRIB,IA(LOC(39)),IADR,LTOP,D2,D3)
C
C   UPDATE AGE OF OFFENDER
      ATRIB(IADR,3)=ATRIB(IADR,3)+TAGE1
C
C   UPDATE CAREER COST
      IF(.NOT.RESC)GO TO 4013
      TCOST=0.
      DO 4012 IRS=1,MRES
        RCOST=MRES(ID,IRS)*KOSTR(IRS)*ST
4012 TCOST=TCOST+RCOST
      ATRIB(IADR,5)=ATRIB(IADR,5)+TCOST
C
4013 IF(ID.EQ.21)GO TO 4021
      IF(ID.EQ.8)GO TO 4020
      RETURN
C
C   ENTER OFFENDER INTO PRE-TRIAL DETENTION
4020 B=RAND(JSEED)
      IF(B.GT.YJAIL(ICRIME))GO TO 4023
      IX=10
      GO TO 4022
4021 B=RAND(JSEED)
      IF(B.GT.AJAIL(ICRIME))GO TO 4023
      IX=22
C   SAVE TIME OFFENDER ENTERS PRE-TRIAL DETENTION
4022 ATRIB(IADR,4)=TNOW
C   INSERT DUMMY ENTITY INTO THE WAITING LIST OF EITHER BOX 10 OR 22
      CALL RELEAS(ID,IX,TRACED,IA(LOC(1)),IA(LOC(3)),IA(LOC(5)),
        * IA(LOC(8)),IA(LOC(9)),IA(LOC(14)),IA(LOC(29)),IA(LOC(30)),
        * IA(LOC(32)),IA(LOC(34)),TNOW,NOMPAS,IP,IA(LOC(2)),
        * IA(LOC(4)),RESC,QUE,COST,ITOP,LTOP,IAVAIL,D2,D3,ISP1),
        RETURNS(9002)
      RETURN
4023 ATRIB(IADR,4)=9999.
      RETURN
C
C   PAROLE VIOLATION, FINISH REMAINDER OF SENTENCE (BOXES 40, 41)
4104 IF(ATRIB(IADR,4).GT.8)GO TO 4105
      ST=ATRIB(IADR,4)

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      ATRIB(IADR,4)=9999.
      GO TO 4010

C
C   DETERMINE SENTENCE DURATION FOR ADULTS IN PRISON OR ON
C   PROBATION USING FINAL CHARGE AND PLEA TYPE (BOXES 40,41,42,26,51)
4105 ICHARG=ATRI(IADR,4)/100.+05
      IF(ICHARG.LE.0 .OR. ICHARG.GT.NCHARG) WRITE(6,8) ID,ICHARG
      8 FORMAT(1H0,*GNS ERROR: AT BOX*,I3,*, FINAL CHARGE IS*,I3)
      JD=AMOD(ATRI(IADR,4),100.)+.001
      IDISP=1
      IF(ID.EQ.42)IDISP=2
      IF(ID.EQ.26.OR.ID.EQ.51)IDISP=3
      IF(JD-37) 4110,4111,4109
4109 ST=TSUR(ICHARG,IDISP)
      GO TO 4112
4110 ST=SDUR(ICHARG,IDISP)
      GO TO 4112
4111 ST=PSUR(ICHARG,IDISP)
4112 A1(5)=ST
      CALL ERLNG(ISEED,ST,A1),RETURNS(9000)
      IF(ID.EQ.40)GO TO 4115
      IF(ID.EQ.41)GO TO 4115
      GO TO 4010

C
C   DETERMINE THE ACTUAL TIME SERVED IN PRISON, STORE NEGATIVE OF
C   REMAINDER OF SENTENCE IN CASE OF PAROLE VIOLATION (ID=40,41)
4115 EST=ST
      ST=PAROLE(ICHARG,1)*EST
      LEFEM=FSEX(IADR)
      IF(LEFEM.EQ.0)ST=PAROLE(NCHARG+ICHARG,1)*EST
      IST=(ST-EST)*1000
      ATRIB(IADR,4)=IST*100-ICHARG
      GO TO 4010

C
C   (ID=45) OFFENDER RELEASED ON PAROLE
4120 B=AND(JSEED)
      ICHARG=-AMOD(ATRI(IADR,4),100.)+.05
      IF(ICHARG.LE.0 .OR. ICHARG.GT.NCHARG) WRITE(6,8) ID,ICHARG
      A3(3)=3600.
      A3(5)=PAROLE(ICHARG,2)
      CALL ERLNG(ISEED,ST,A3),RETURNS(9000)
      PAR=PAROLE(ICHARG+NCHARG,2)
      IF(B.GT.PAR)GO TO 4121
C   PAROLE VIOLATION: RETURN TO PRISON
      IST=ATRI(IADR,4)/100.
      ATRIB(IADR,4)=FLOAT(IST)/1000.
      GO TO 4010
C   NO PAROLE VIOLATION: COMPLETE PAROLE
4121 ATRIB(IADR,4)=9999.
      GO TO 4010

C
C   DETERMINE RECIDIVISM DELAY, UPDATE AGE OF OFFENDER (BOXES 19,47,48)
4500 A3(3)=10**5
      A3(5)=ATRI(IADR,4)
      CALL ERLNG(ISEED,ST,A3),RETURNS(9000)

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TAGE1=ST/360.
TAGE=AGE+TAGE1
DAGE=FDEATH(IADR)
IF(TAGE.LT.DAGE)GO TO 4501
ST=.05*ST
IF(DAGE.GT.AGE) ST=(DAGE-AGE)*360.
TAGE1=ST/360.
ATTRIB(IADR,3)=AMOD(ATTRIB(IADR,3),100000.)
4501 ATTRIB(IADR,3)=ATTRIB(IADR,3)+TAGE1
ATTRIB(IADR,1)=TNOW+ST
CALL SORT(6,ATTRIB,IA(LOC(39)),IADR,LTOP,D2,03)
RETURN

C
C DETERMINE NEW OFFENSE FOR REPEAT OFFENDER (BOXES 20,49)
4600 B=RAND(JSEED)
DO 4601 J=1,NCRIME
IF(B.LE.SWITCH(ICRIME,J))GO TO 4602
4601 CONTINUE
J=NCRIME
4602 IF(TNOW.GE.DINITL) RARREST(J)=RARREST(J)+1
NARREST=.05+AMOD(ATTRIB(IADR,6),100.)
NARREST=NARREST+1
LCRIME=J*10*(NARREST+1)
ATTRIB(IADR,6)=ATTRIB(IADR,6)+LCRIME+1
RACEX=FRACEX(IADR)
IDAGE=ATTRIB(IADR,3)/100000.+.05
ATTRIB(IADR,3)=IDAGE*100000+J*10000+RACEX*1000+AGE
RETURN

C
C COLLECT STATISTICS AT SINK NODES
C (OFFENDER EITHER DIES OR HE IS REHABILITATED)
4900 IF(TNOW.LT.DINITL) GO TO 4990
IPRED=ATTRIB(IADR,4)+.05
ICOF5=ICOF5+1

C
C COLLECT OFFENDER CATEGORY (RACE & SEX) STATISTICS
RACEX=FRACEX(IADR)
IF(RACEX.GE.1.OR.RACEX.LE.NOC) GO TO 4901
WRITE(6,4) RACEX,ID,IPRED
4 FORMAT(1H0,*CJS ERROR: OFFENDER CATEGORY =*,I4,* AT SINK NODE*,
* I4,* PRECEDED BY BOX*,I4)
GO TO 4902
4901 ICOF(RACEX)=ICOF(RACEX)+1
IB=NP(20)+RACEX
IUDATA(IB)=ISTAT(1,RACEX,1)+1

C
C COLLECT AGE HISTOGRAM
4902 I=AGE/5.+1.
SAGE(RACEX)=SAGE(RACEX)+AGE
IMAX=IUDATA(NP(31))
IF(I.GT.1.AND.I.LE.IMAX) GO TO 4903
WRITE(6,5) AGE,ID,IPRED
5 FORMAT(1H0,*CJS ERROR: OFFENDER AGE =*,F8.2,* AT SINK NODE*,
* I4,* PRECEDED BY BOX*, I4)
I=IMAX

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4903 IB=NP(31)+I+(RACEX-1)*IUDATA(NP(31))
    IUDATA(IB)=ISTAT(12,I,RACEX)+1
C
C    COLLECT THE DEATH AGE FOR HISTOGRAM
DAGE=FDEATH(IADR)
IF(DAGE.GT..1) I=DAGE/5.+1
IF(I.GT.1.AND.I.LE.IMAX) GO TO 4904
WRITE(6,10) DAGE,IO,IPRED
10 FORMAT(1H0,'CJS ERROR: OFFENDER DEATH AT AGE =*,F8.2,
* * AT SINK NODE*,I4,* PRECEDED BY BOX*,I4)
I=IMAX
4904 IB=NP(21)+I+(RACEX-1)*IUDATA(NP(21))
    IUDATA(IB)=ISTAT(2,I,RACEX)+1
C
C    COLLECT NUMBER OF OFFENSES COMMITTED FOR TIME SERIES
IC=ATRI8(IADR,6)+.05
NOFS=MOD(IC,100)
IB=NP(23)+NOFS+(RACEX-1)*IUDATA(NP(23))
IUDATA(IB)=ISTAT(4,NOFS,RACEX)+1
SNOFS(RACEX)=SNOFS(RACEX)+NOFS
ANOFS(RACEX,ICRIME)=ANOFS(RACEX,ICRIME)+NOFS
NO(RACEX,ICRIME)=NO(RACEX,ICRIME)+1
C
C    COLLECT OFFENSE TYPES FOR HISTOGRAM
DO 4909 I=1,NOFS
J=10*(I+1)
K=10*(I+2)
IO1=MOD(IC,K)
IO=IO1/J
IF(IO.GE.1.AND.IO.LE.NCRIME)GO TO 4908
WRITE(6,25) IO,IPRED,IC,K,IO1,J,IO
25 FORMAT(* GNS ERROR: SINK=*,I5,* PREDECESSOR=*,I5,* MOD(*,I10,
* *,*,I10,*) =*,I10,* DIVIDED BY*,I10,* EQUALS *,I10)
IO=7
4908 IB=NP(22)+IO+(RACEX-1)*IUDATA(NP(22))
4909 IUDATA(IB)=ISTAT(3,IO,RACEX)+1
C
C    COLLECT SINK BOX NUMBERS FOR HISTOGRAM
DIO=ID/10+1
GO TO (4920, 4921, 4922, 4923, 4924), DIO
4920 I=1
IF(ID.EQ.7)I=2
GO TO 4925
4921 I=3
GO TO 4925
4922 I=4
GO TO 4925
4923 I=ID-29
GO TO 4925
4924 I=8
4925 IB=NP(24)+I+(RACEX-1)*IUDATA(NP(24))
    IUDATA(IB)=ISTAT(5,I,RACEX)+1

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C
C   ACCUMULATE CAREER CRIMINAL COST FOR MONTHLY AVERAGE
CCC=ATRI8(IADR,5)
SCCC(RACEX)=SCCC(RACEX)+CCC
C
C   STORE CAREER CRIMINAL COST HISTOGRAM
I=CCC/DCCC+1
IMAX=IUDATA(NP(25))
IF(I.LE.IMAX) GO TO 4930
I=IMAX
4930 IB=NP(25)+I+(RACEX-1)*IUDATA(NP(25))
IUDATA(IB)=ISTAT(6,I,RACEX)+1
C
C   TERMINATE SIMULATION
4990 YEAR=TNOW/360+.001
IF(YEAR.LT.TSTOP) RETURN
IPASS=0
IF(IERRS.LE.0) WRITE(6,3) TNOW, ICOFS, TINITL, LADR
3  FORMAT(1H0,*AT TIME*,F10.2,3X,*SIMULATION RUN SUCCESSFULLY*,
*   * TERMINATES WITH *,I5,* SINK NODES REALIZED SINCE TINITL = *
*   * , F6.2/21X,*LARGEST OFFENDER ADDRESS IS*,I5)
IF(IERRS.GT.0) WRITE(6,26) TNOW
26  FORMAT(1H0,*AT TIME*,F10.2,3X,*SIMULATION TERMINATES*)
NARREST=0
DO 4995 IK=1,NCRIME
4995 NARREST=NARREST+IARREST(IK)
WRITE(6,1) TINITL, NARREST
1  FORMAT(1H0,20X,*THE TOTAL NUMBER OF FIRST-OFFENSE ARRESTS AFTER *,
*   * F6.2,* IS*,I10)
NARREST=0
DO 4996 IK=1,NCRIME
4996 NARREST=NARREST+RARREST(IK)
WRITE(6,13) TINITL, NARREST
13  FORMAT(21X,*THE TOTAL NUMBER OF RECIDIVIST   ARRESTS AFTER *,
*   * F6.2,* IS*,I10/1H0)
WRITE(6,14) (I,CRIME(I),IARREST(I),RARREST(I),I=1,NCRIME)
14  FORMAT(20X,* FOR CRIME*,I2,* ( *,A10,* ), *,I10,* FIRST-OFFENSE*,
** ARRESTS AND*,I10,* RECIDIVIST ARRESTS ARE MADE*)
RETURN
C
C   #####
C   END CONTROL LOGIC
C   #####
C
5000 AGE=FAGE(IADR)
ICRIME=FCRIME(IADR)
C
C   IF DECEASED, GO TO BOX 3 & COLLECT STATISTICS
DAGE=FDEATH(IADR)
IF(DAGE.GT..1)GO TO 5002
ATRI8(IADR,4)=ID+.001
NN=3
RETURN
C

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```

5002 GO TO (8000,5102,8000,8000,5105,8000,8000,5006,5006,8000,
*      8000,5114,5114,5114,5114,8000,8000,8000,8000,5102,
*      8000,8000,5700,8000,5320,5120,8000,5006,5116,5700,
*      5116,5700,8000,8000,8000,8000,5300,8000,5400,5123,
*      5123,5125,5120,5120,5121,8000,8000,8000,5006,5120,
*      5120,5600,5601,5614,8000,5610,5615), ID
C
C      PROBABILISTIC SELECTION OF SUCCESSOR BOX, NN, TO BE RELEASED
5006 CALL LOCF(ID,1,LOCP,LOCPP)
      IC=0
      J=IPARC(ID)*1
      B=Rand(JSEED)
      DO 5003 IND=LOCP,LOCPP
      BAL=UDATA(J+NCRIME*IC+ICRIME)
      IF(B.LE.BAL)GO TO 5004
      IC=IC+1
5003 CONTINUE
      IND=LOCPP
5004 NN=IA(IND)
      IF(ID.EQ.9)GO TO 5500
      IF(ID.EQ.8.AND.NN.NE.9)GO TO 5500
      IF(NN.LT.52) RETURN
      ATRIB(IADR,4)=ID+.001
      RETURN
C
C      ADDITIONAL END CONTROL LOGIC:
C
C      ID=2,20
5102 IF(AGE.GE.ADULT)GO TO 5006
      NN=5
      RETURN
C
C      ID=5
5105 NN=8
      IF(AGE.GE.ADULT)NN=21
      RETURN
C
C      ID=12,13,14,15
5114 NN=53
      ATRIB(IADR,4)=ID+.001
      RETURN
C
C      ID=29,31
5116 NN=54
      GO TO 5500
C
C      ID=26,43,44,50,51
5120 NN=57
      ATRIB(IADR,4)=ID+.001
      RETURN
C
C      ID=45: PAROLE TERMINATED W/O VIOLATIONS, RELEASE OFFENDER FROM CJS
5121 IF(ATRIB(IADR,4).LE.0.)GO TO 5122
      NN=56
      ATRIB(IADR,4)=ID+.001
      RETURN

```



```

C
C      ID=45: PAROLE VIOLATION, RETURN OFFENDER TO PRISON TO COMPLETE SEN
5122 LEFEM=FSEX(IADR)
      NN=40
      IF(LEFEM.EQ.0) NN=41
      RETURN
C
C      ID=40,41: INCARCERATION TERMINATED, RELEASE OFFENDER FROM CJS
5123 IF(ATTRIB(IADR,4).LT.0.) GO TO 5124
      NN=56
      ATTRIB(IADR,4)=ID+.001
      RETURN
C
C      EARLY RELEASE FROM PRISON OFFENDER IS ON PAROLE
5124 NN=45
      RETURN
C
C      ID=42
5125 NN=56
      ATTRIB(IADR,4)=ID+.001
      RETURN
C
C      DETERMINE THE SUPERIOR COURT DISPOSITION AFTER A GUILTY PLEA
5300 B=RAND(JSEED)
      DO 5301 ICHARG=1,NCHARG
      BAR=BARGAN(ICRIME,ICHARG)
      IF(B.LE.BAR) GO TO 5302
5301 CONTINUE
      ICHARG=NCHARG
5302 B1=RAND(JSEED)
      DO 5303 IDISP=1,NDISP
      BAR1=PDISP(ICHARG,IDISP)
      IF(B1.LE.BAR1) GO TO 5404
5303 CONTINUE
      IDISP=NDISP
      GO TO 5404
C
C      DETERMINE LOWER COURT'S DISPOSITION
5320 B=RAND(JSEED)
      DO 5321 IDISP=1,NDISP
      BAR=DISPL(ICRIME,IDISP)
      IF(B.LE.BAR) GO TO 5322
5321 CONTINUE
      IDISP=NDISP
5322 ICHARG=ICRIME
      GO TO 5404
C
C      DETERMINE SUPERIOR COURT TRIAL DISPOSITION
5400 B=RAND(JSEED)
      DO 5401 ICHARG=1,NCHARG
      BAR=CONVIC(ICRIME,ICHARG)
      IF(B.LE.BAR) GO TO 5402
5401 CONTINUE
      ICHARG=NCHARG
5402 B1=RAND(JSEED)

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      DD 5403 IDISP=1,NDISP
      BAR1=TDISP(ICHARG,IDISP)
      IF(B1.LE.BAR1)GO TO 5404
5403 CONTINUE
      IDISP=NDISP
5404 IT=ATRI(IADR,4)+.05
      ATRIB(IADR,4)=ICHARG*100+ID+.05
      LEFEM=FSEX(IADR)
5410 GO TO (5411,5412,5413,5414,5415,5416),IDISP
5411 NN=40
      IF(LEFEM.EQ.0)NN=41
      GO TO 5501
5412 NN=42
      GO TO 5501
5413 NN=50
      GO TO 5501
5414 NN=43
      GO TO 5501
5415 NN=44
      GO TO 5501
5416 NN=26
      IF(LEFEM.EQ.0)NN=51
      GO TO 5501
C
C LOCATE OFFENDER DETAINED BEFORE TRIAL
5500 IT=ATRI(IADR,4)+.05
5501 IF(IT.GE.0)GO TO 5502
      IF(NN.LT.52) RETURN
      ATRIB(IADR,4)=ID+.001
      RETURN
5502 KADR=LTOP
      KD=22
      IF(ID.EQ.8.OR.ID.EQ.9)KD=10
5503 IF(KADR.GT.8)GO TO 5505
      MES1=10HUNABLE TO
      MES2=10HLOCATE DET
      MES3=10HAINED OFFE
      MES4=10HNDER
      CALL ERRSIN(ID,KD,SUBN,MES1,MES2,MES3,MES4), RETURNS(9000,9002)
5504 KADR=NEXT(KADR)
      GO TO 5503
5505 IF(LIST(KADR).NE.KD)GO TO 5504
      IJ=ATRI(KADR,4)+.05
      IF(IJ.NE.IT)GO TO 5504
C
C UPDATE CAREER CRIMINAL COST DUE TO PRE-TRIAL DETENTION
      ST=TNOW-ATRI(KADR,4)
      TCOST=0.
      DO 5506 IRS=1,MRES
      RCOST=NRES(KD,IRS)*KOSTR(IRS)*ST
5506 TCOST=TCOST+RCOST
      ATRIB(IADR,5)=ATRI(IADR,5)+TCOST
C
C REMOVE OFFENDER FROM PRE-TRIAL DETENTION
      ATRIB(KADR,1)=TNOW
      CALL SORT(6,ATRI,IA(LOC(39)),KADR,LTOP,D2,D3)

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      IF(NTRACE.GT.0) GO TO 5507
      IF(TRACE) WRITE(6,9) TNOW,KD,KADR,NOWPAS
9  FORMAT(* AT TIME*,F10.2,*  ACTIVITY*,I7,*  (AT LIST LOCATION*,
      *  I7,*)  COMPLETED  ON RUN*,I7)
C
5507 IF(NN.EQ.23)GO TO 5520
      IF(NN.LT.52) RETURN
      ATRIB(IADR,4)=ID+.001
      RETURN
C
C  JUVENILE IS TRIED AS AN ADULT
5520 B=Rand(JSEED)
      BAR=AJAIL(ICRIME)
      IF(B.LE.BAR)GO TO 5521
C  JUVENILE IS NOT DETAINED BEFORE TRIAL AS AN ADULT
      ATRIB(IADR,4)=-9999.
      RETURN
C
C  JUVENILE IS DETAINED AS AN ADULT
5521 ATRIB(IADR,4)=TNOW
      IX=22
      CALL RELEAS(ID,IX,TRACE,IA(LOC(1)),IA(LOC(3)),IA(LOC(5)),
      *  IA(LOC(8)),IA(LOC(9)),IA(LOC(14)),IA(LOC(29)),IA(LOC(38)),
      *  IA(LOC(32)),IA(LOC(34)),TNOW,NOWPAS,IP,IA(LOC(2)),
      *  IA(LOC(4)),RESC,QUE,COST,ITOP,LTOP,IAVAIL,D2,D3,ISP1),
      *  RETURNS(8002)
      RETURN
C
C  DETERMINE IF JUVENILE OFFENDER RECIDIVATES
C  ID=52
5600 IREL=3
      IFOL=19
      NN=7
      GO TO 5620
C  ID=53
5601 IPRE=ATRIB(IADR,4)+11
      IFOL=19
      NN=18
      GO TO (5605, 5602, 5604, 5603), IPRE
5602 IREL=1
      GO TO 5620
5603 IREL=2
      GO TO 5620
5604 IREL=4
      GO TO 5620
5605 IREL=5
      GO TO 5620
C
C  DETERMINE IF ADULT OFFENDER RECIDIVATES
C  ID=56
5610 IPRE=ATRIB(IADR,4)
      IF(IPRE=42) 5613, 5612, 5611
5611 NN=46
      IFOL=47
      IREL=4

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      GO TO 5620
5612 IFOL=47
      IREL=1
      NN=36
      GO TO 5620
5613 IREL=5
      NN=46
      IFOL=47
      GO TO 5620
C      ID=54
5614 IFOL=48
      IREL=3
      NN=27
      GO TO 5620
C      ID=57
5615 IFOL=48
      IPRE=ATTRIB(IADR,4)
      IF(IPRE.NE.26.AND.IPRE.NE.51)GO TO 5616
      NN=34
      IREL=5
      GO TO 5620
5616 NN=35
      IF(IPRE=44) 5618, 5617, 5619
5617 IREL=1
      GO TO 5620
5618 IREL=2
      GO TO 5620
5619 IREL=3
C
C      DETERMINE IF OFFENDER RECIDIVATES
5620 B=RAND(JSEED)
      IAGE=AGE/5.-2.
      IF(IAGE.LE.0)IAGE=1
      IF(IAGE.GE.7)IAGE=IAGE-1
      IF(IAGE.GE.8)IAGE=7
      LEFEM=FSEX(IADR)
      ISEX=LEFEM+1
      C=RECID(0,IAGE,ISEX)
      IF(B.GT.C)RETURN
      NOFS=ATTRIB(IADR,6)+.05
      NOFS=MOD(NOFS,100)
      IB=NP(23)
      IF(NOFS.GE.IUDATA(IB)) RETURN
      NN=IFOL
      ATTRIB(IADR,4)=RECID(1,IAGE,IREL)
      RETURN
C
C      THE PROSECUTOR EFFECTS THE FLOW OF OFFENDERS THRU THE COURTS
C      BOXES 23,30,32
C
5700 CALL LOCF(ID,1,LOCP,LOCPP)
      IC=0
      J=IPARC(ID)-1
      DO 5701 I=LOCP,LOCPP
      IB=IC+1
      PI(IB)=UDATA(J+NCRIME*IC+ICRINE)

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5701 IC=IC+1
    IF(TNOM.LT.TINITL*360.) GO TO 5706
C
C    LEVEL OF PROSECUTOR'S RESOURCES EFFECTS HIS DECISIONS
    PROBM1=RR
    PROBM2=RR
    IF(MERES.EQ.1) PROBM2=1.
    IF(MERES.EQ.2) PROBM1=1.
C
C    THE SIZE OF THE PRE-TRIAL DELAY EFFECTS THE PROSECUTOR'S DECISIONS
    IF(MEQUE.LE.0) GO TO 5704
    SWAIT=NWAIT(37)+NWAIT(39)
5702 IF(SWAIT.LE.0.) GO TO 5704
5703 IF(MEQUE.NE.2) PROBM1=PROBM1*SINITQ/SWAIT
    IF(MEQUE.GE.2) PROBM2=PROBM2*SWAIT/SINITQ
C
C    THE SEVERITY OF THE CURRENT OFFENSE EFFECTS THE PROSECUTOR'S DECISIONS
5704 IF(MESEV.LE.0) GO TO 5705
    CSR=SEVERE(ICRIME)/ACS
    IF(MESEV.NE.2) PROBM1=PROBM1*CSR
    IF(MESEV.GE.2) PROBM2=PROBM2*CSR
C
C    THE DEFENDANT'S CRIMINAL HISTORY EFFECTS THE PROSECUTOR'S DECISIONS
5705 IF(MEHIS.LE.0) GO TO 5706
    CON=AMOD(ATRIB(IADR,6),100.)
    CHM=CON/ANO(ICRIME)
    IF(MEHIS.NE.2) PROBM1=PROBM1*CHM
    IF(MEHIS.GE.2) PROBM2=PROBM2*CHM
C
5706 IF(ID=30) 5710,5720,5730
C
C    ADJUST PROSECUTOR'S PROBABILITIES AT BOX 23
5710 PI(2)=PI(2)*PROBM1
    PI(2)=AMIN1(PI(2),1.0)
    B=RAND(JSEED)
    IF(B.GT.PI(2)) GO TO 5711
    NN=28
    RETURN
5711 DP=1+PI(2)
    DPA=PI(1)/(PI(1)+PI(3))
    PI(1)=DP*DPA+PI(2)
    NN=25
    IF(B.LE.PI(1)) GO TO 5740
    NN=54
    GO TO 5500
C
C    ADJUST PROSECUTOR'S DECISION PROBABILITIES AT BOX 30
5720 PI(2)=PI(2)*PROBM1
    PI(2)=AMIN1(PI(2),1.0)
    NN=32
    B=RAND(JSEED)
    IF(B.GT.PI(2)) NN=31
    RETURN

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C      ADJUST PROSECUTOR'S DECISION PROBABILITIES AT BOX 32
C      5730 PI(2)=PI(2)*PROBM2
          PI(2)=AMIN1(PI(2),1.0)
          NN=39
          B=RAND(JSEED)
          IF(B.GT.PI(2))NN=37

C      DETERMINE WHETHER OR NOT DETAINED OFFENDER IS STILL IN JAIL DURING
C      A TRIAL AT ANY OF BOXES 25,37,39
C      5740 IT=ATRI(ADR,4)+.05
          IF(IT.LT.0) RETURN
          B=RAND(JSEED)
          IF(B.LE.CJAIL(ICRIME)) RETURN
          ATRI(ADR,4)=-9999.
          KADR=LTOP
          KD=22
          GO TO 5503

C      #####
C      ILLEGAL CALL TO USERC SUBROUTINE
C      #####
C
C      8000 MES1=10HILLEGAL CA
          MES2=10HLL TO USER
          MES3=10HC: BOX NU
          MES4=10HMBER ERROR
          CALL ERRSIM(ID,-N,SUBN,MES1,MES2,MES3,MES4), RETURNS(9000,9002)
C      8001 ITO=5
          MES1=10HILLEGAL CA
          MES2=10HLL TO USER
          MES3=10HC
          MES4=10H
          CALL ERRSIM(0,N,SUBN,MES1,MES2,MES3,MES4), RETURNS(9000,9002)
C      8002 ITO=5
          MES1=10HRELEASE OF
          MES2=10H JUVENILE
          MES3=10HJAILED AS
          MES4=10HADULT
          CALL ERRSIM(0,ID,SUBN,MES1,MES2,MES3,MES4), RETURNS(9002,9002)
C
C      9000 RETURN
C      9001 RETURN MQXI
C      9002 RETURN MXYZ
          END

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C*****
C
      SUBROUTINE USERD(D1,D2,D3,D4,D5,D6,D7,D8,D9,MRES,LOCRES,IFREQ,
      *ATTRIB,IATTRIB,TS)
C
C      PURPOSE:  TO OUTPUT SPECIAL USER VARIABLES AND REPORTS
C                AT THE END OF SIMULATION.
C*****
C
      COMMON/CJS/NCRIME,CRIME,NCHARG,NDISP,MSOISP,DUMP,NPN,ADULT,NOC,
      *MBEGIN,ACS,PRG,MEQUE,MERES,MESEV,MEHIS,MIS,MONTHS,IYEARS,
      *DCCC,MICCC,SCCC,SNOFS,ICOF,TSTOP,TINITL,IERROR,ANO,TRACEF,
      *ANOF5(4,7),NO(4,7),RSUM(10),RSQ(10),RMAX(10),RNUM,RTIME,SAGE
      *,RGROW(10),SINITQ
      COMMON/BASE/ARRAY(58000),UDATA(3000)
      COMMON/GLOBAL/C1,C2,C3,FSHOT,IR,IP,IGO,IFROM,ITS1,IFR1,IAVAIL,
      *IDRUN,ITO,IRATE,ISTUP,IPRTY,ISPSEG,IFULL,ISP1,ISP8,ISP9,
      *ISP10,ISP11,ISP12,ISP15,ISP21,IP1,IP2,IP3,IP4,IP5,IP6,
      *IP7,IP8,IP9,IP10,IP11,ISEED,ITOP,IP15F,IP15,IP16,IP17,
      *IP18,IP19,IP20,IP21,IP22,IP23,IP24,JHALF,K,LOC2,
      *MAXAR,MAXUD,MAXIA,MAXIO,MHST,MENTRY,MRES,NBOX,MRES1,
      *MHRES,MDELET,MWORK,MV,MCELL,NQBOX,MFVAR,NST,
      *NERR,NOHPAS,NPASS,NBOX,NGRP,METRL,NTRACE,NCALL,NSINK,
      *NQB1,NQB2,NSOUR,NBOX,NRBOX,NATRIB,MCELL,TCALL,UTIME,
      *ISW1,ISW2,ISW3,ISW4,ISW5,VAR1,VAR2,VAR3,VAR4,VAR5,LINE,
      *NRATE,IWRITE,IPASS,KSUM,LTOP,TNOW,TLAST,
      *NODMP,CONT,COST,END,NXTHOD,QUE,RESC,RESCHG,SEPRT,
      *STDEP,TMCOST,UIIN,UOUT,UFORM,STCHG,NOPREM,LU1,LU2,LU3,LU4,
      *LU5,LU6,LU7,LU8,LU9,LU10,LLAG,LLSEGM,LORS
C
      LOGICAL LU1,LU2,LU3,LU4,LU5,LU6,LU7,LU8,LU9,LU10,LLAG,
      *LLSEGM,LORS
      LOGICAL CONT,COST,END,NXTHOD,QUE,RESC,RESCHG,SEPRT,
      *STDEP,TMCOST,UIIN,UOUT,UFORM,STCHG,NOPREM,NODMP
C
      INTEGER D1,D2,D3,D4,D5,D6,D7,D8,D9,SUBN
      INTEGER NEH(12),NHIST(5,12),CRIME(7),SINKS(8)
      INTEGER MRES(D1,D4),IFREQ(D8,D9),LOCRES(D4,D5),IATTRIB(D2,D3),
      *IA(58000),IUDATA(3000),LOC(100),NP(100),NEX(15)
C
      REAL ATTRIB(D2,D3),TS(D6,D7),A(58000)
      REAL HMIN(12),HINC(12),ANO(7),ICOF(4),SCCC(4),SNOFS(4),SAGE(4)
      LOGICAL DUMP,TRACEF
C
      EQUIVALENCE (IA(1),A(1),ARRAY(1),LOC(1)),
      *(UDATA(1),IUDATA(1),NP(1))
C
      DATA SUBN/8HUSERD /
      DATA (NHIST(I,1),I=1,4) /10HOFFENDER C,10HATEGORIES ,
      * 10H(1=MALE, 2,10H=FEMALE) /
      DATA (NHIST(I,2),I=1,2) /10HOFFENDER D,10HEATH AGE /
      DATA (NHIST(I,3),I=1,2) /10HOFFENSES C,10HOMMITTED /
      DATA (NHIST(I,4),I=1,4) /10HNUMBER OF ,10HOFFENSES P,
      * 10HER OFFENDE, 1HR /

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DATA (NHIST(I,5),I=1,3) /10HSINK BOX R,10HEALIZATION,
* 1HS /
DATA (NHIST(I,6),I=1,3) /10HCAREER CRI,10HMNIAL COST,
* 10H (/ICCC) /
DATA (NHIST(I,7),I=1,4) /10HTIME SERIE,10HS OF CAREE,
* 10HR CRIMINAL,10H COST /
DATA (NHIST(I,8),I=1,5) /10HTIME SERIE,10HS OF NUMBE,
* 10HR OF OFFEN,10HSES PER OF,
* 10HFENDER /
DATA (NHIST(I,9),I=1,5) /10HTIME SERIE,10HS OF (CARE,
* 10HER COST)/(,10HNUMBER OF ,
* 10HOFFENSES) /
DATA (NHIST(I,10),I=1,4) /10HTIME SERIE,10HS OF AVERA,
* 10HGE AGE OF ,10HOFFENDER /
DATA (NHIST(I,11),I=1,3) /10HINITIAL AG,10HE OF OFFEN,
* 10HDER /
DATA (NHIST(I,12),I=1,3) /10HFINAL AGE ,10HOF OFFENDE,
* 10HR /
DATA NEH /4, 2, 2, 4, 3, 3, 4, 5, 5, 4, 3, 3/
DATA HMIN /1., 5., 1., 1., 1., 1., 0., 0., 0., 0., 5., 5./
DATA HINC /1.,5.,1.,1.,1.,1.,180.,180.,180.,180.,5.,5./
DATA SINKS/ 3, 7, 18, 27, 34, 35, 36, 46/
DATA NEX/4,5,1,2,14,8,9,10,11,7,13,3,15,6,16/

```

C  
C  
C  
C  
C  
C

```

#####
BEGINNING OF RUN: REPORT CJS PARAMETERS
#####

```

C  
C

```
IF(TNOW.GE.38.)GO TO 68
```

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C
IADULT=ADULT
PRR=PRG*188.
ICCC=DCCC
IF(DUMP) WRITE(6,18)
10 FORMAT(1H1)
WRITE(6,1)NCRIME,NCHARG,NDISP,NSDISP,NOC,IADULT,
* ICCC,MICCC,ACS,TSTOP,MBEGIN,PRR,NP(NPN)
1 FORMAT(1H0,35X,*CRIMINAL JUSTICE MODEL INPUT DATA*/1H0/
* * NUMBER OF CRIMES:*,I5/
* * NUMBER OF CONVICTION LABELS:*,I5/
* * NUMBER OF COURT DISPOSITIONS:*,I5/
* * NUMBER OF DISPOSITIONS REQUIRING CJS MONITORING:*,I5/
* * NUMBER OF OFFENDER CATEGORIES:*,I5/
* * MINIMUM AGE OF ADULTS:*,I5/
* * DIVISOR FOR CAREER CRIMINAL COST:*,I8/
* * MAX. NUMBER OF HISTOGRAM BARS FOR CAREER CRIMINAL COST:*,
* I5/
* * AVERAGE CRIME SEVERITY VALUE:*,F10.2/
* * NUMBER OF YEARS SIMULATED:*,F8.2/
* * MONTH PROSECUTOR'S RESOURCES AND/OR INFORMATION*,
* ARE CHANGED:*,I5/
* * PERCENT CHANGE IN THE PROSECUTOR'S RESOURCES:*,F7.2/
* * ACTUAL SIZE OF USER ARRAY:*,I6)

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C



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      IF(TINITL.GT.0.) WRITE(6,6) TINITL
6  FORMAT(* YEAR TO BEGIN COLLECTING CJS STATISTICS:*,F8.2)
   WRITE(6,28) (RGROW(IG),IG=1,MRES)
28  FORMAT(* RESOURCE LEVEL MONTHLY GROWTH RATES:*,10F18.3//)
      INFO=MESEV+MEHIS
      IPLEA=INFO+MEQUE+MERES
      IF(IPLEA.LE.0) GO TO 30
      IF(INFO.LE.0) GO TO 40
      WRITE(6,3) MIS
3  FORMAT(* COST PER OFFENDER OF CAREER CRIMINAL INFORMATION: $*,I5)
   IF(MESEV.GT.0) WRITE(6,11)
11  FORMAT(* CRIME SEVERITY EFFECTS PROSECUTOR'S DECISIONS*)
   IF(MEHIS.GT.0) WRITE(6,12)
12  FORMAT(* OFFENDER'S PREVIOUS CRIMINAL RECORD EFFECTS*,
*         * PROSECUTOR'S DECISIONS*)
      IF(MEHIS.GT.0) WRITE(6,16) (I,ANO(I),I=1,NCRIME)
16  FORMAT(10X,*AVERAGE NUMBER OF OFFENSES OF ALL*,
*         * OFFENDERS WHO COMMIT CRIME*,I3,* IS*,F8.2)
40  IF(MEQUE.GT.0) WRITE(6,13)
13  FORMAT(* LENGTH OF PRE-TRIAL DELAY EFFECTS PROSECUTOR'S*,
*         * DECISIONS*)
      IF(MEQUE.GT.0) WRITE(6,29) SIMITQ
29  FORMAT(* BASE VALUE OF SUPERIOR COURT PRE-TRIAL QUEUE:*,F5.0)
   IF(MERES .GT. 0) WRITE(6,14)
14  FORMAT(* LEVEL OF PROSECUTOR'S RESOURCES EFFECTS HIS*,
*         * DECISIONS*)
C
30  IF(DUMP) GO TO 50
   WRITE(6,15)
15  FORMAT(1H1,35X,*GNS MODEL INPUT PARAMETERS*)
   GO TO 1000
C
C #####
C BEGINNING OF RUN: DUMP USER ARRAYS
C #####
C
50  WRITE(6, 5)
5  FORMAT(1H1,35X,
*  *THE FOLLOWING IS A DUMP OF USER-SUPPLIED DATA: *)
   WRITE(6,4) NP(NPN),NAXUD
4  FORMAT(/1H0,25X,* SIZE REQUIRED FOR USER ARRAY:*,I6,
*         * SIZE ALLOCATED:*,I6/1H0)
   NPN1=1
   GO TO 75
C
60  WRITE(6,9)
9  FORMAT(1H1,55X,* USER HISTOGRAMS*)
   NPN1=20
C
75  NPNF=NPN-1
   DO 90 I=NPN1,NPNF
     J=I+1
     L=J
     IF(I.LE.15) L=MEV(I)
     K=NP(L)-NP(I)

```

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      WRITE(6,2) J,I,K
2  FORMAT(1H0/25X,* PARTITION *,I2,* BEGINNING AT NP(*,I2,
* *) CONTAINS*, I4,* ELEMENTS*/ )
      IF=NP(I)
      IT=NP(L)-1
      IF(I.LT.3)GO TO 80
      IF(I.GE.20.AND.I.LE.25)GO TO 80
      IF(I.GE.30) GO TO 80
      IF(I.EQ.13)IT=NP(L)-2
      WRITE(6,18)(UDATA(J),J=IF,IT)
18  FORMAT(5X,10F10,3)
      IF(I.NE.13)GO TO 90
      IF=NP(L)-1
      IT=IF
80  WRITE(6,19)(IUDATA(J),J=IF,IT)
19  FORMAT(5X,10I10)
90  CONTINUE
C
      IF(TNOW.GE.30.) GO TO 100
      WRITE(6,15)
      GO TO 1000
C
C  #####
C  COMPLETION OF RUN:  OUTPUT GRAPHS OF USER STATISTICS
C  #####
C
100 DO 110 ICRIME=1,NCRIME
    DO 110 IB=1,NOC
110  ANOFS(IB,ICRIME)=ANOFS(IB,ICRIME)/FLOAT(NC(IB,ICRIME))
C
      NPN1=20
      NPNF=NPN-1
      DO 200 I=NPN1,NPNF
      K=I+1
      J=I+19
C
      IF(I.LE.25) GO TO 130
      IF(I.GE.30) GO TO 130
C
C  PRINT TIME SERIES
      IF(TINITL.LE.0.) GO TO 120
      MON=12.*TINITL+6.05
      HMIN(J)=MON*30
120 DO 125 IB=1,NOC
      IADR=(IB-1)*IYEARS+NP(I)
      CALL TOUT(1,1,IYEARS,UDATA(IADR),6,HMIN(J),HINC(J))
      NEHSTOP=NEH(J)
      WRITE(6,8) K,(NHIST(L,J),L=1,NEHSTOP)
125 WRITE(6,27) IB
27  FORMAT(52X,*OFFENDER CATEGORY*,I2)
    GO TO 200
C
C  COMPUTE FREQUENCIES
130 NQUIT=NOC
    IF(K.EQ.21) NQUIT=1
    N1=NP(I)+1

```

```

      N2=N1+IUDATA(NP(I))+1
      DO 190 IB=1,NQUIT
      NSAMPLE=0
      DO 131 L=N1,N2
131  NSAMPLE=NSAMPLE+IUDATA(L)
      IF(NSAMPLE.LE.0) GO TO 180
      DO 132 L=N1,N2
132  IUDATA(L)=100.*IUDATA(L)/NSAMPLE
C
C      PRINT HISTOGRAMS OF STATISTICS
      CALL HISOUT(1,1,IUDATA(NP(I)),IUDATA(N1),HMIN(J),HINC(J),6)
      NEHSTOP=NEH(J)
      WRITE(6,8) K,(NHIST(L,J),L=1,NEHSTOP)
      8  FORMAT(1H0,45X,I3,*,*,5A10)
      WRITE(6,27) IB
      WRITE(6,7) NSAMPLE
      7  FORMAT(1H0,51X,*SAMPLE SIZE = *,I10/1H0)
      IF(J.EQ.3) WRITE(6,20) (ICR,CRIME(ICR),ICR=1,NCRIME)
20  FORMAT(55X,* CRIME*,I2,* = *,A10)
      IF(J.EQ.4) WRITE(6,23) (CRIME(ICR),ANOF5(IB,ICR),NO(IB,ICR),
      * ICR=1,NCRIME)
23  FORMAT(35X,*AVE. NUMBER OF OFFENSES WHEN LAST CRIME IS *,A18,
      * * = *,F8.2,* N = *,I10)
      IF(J.EQ.5) WRITE(6,21) (ISN,SINKS(ISN),ISN=1,8)
21  FORMAT(51X,* SINK*,I2,* = NODE *,I3)
      ICCC=DCCC
      IF(J.EQ.6) WRITE(6,22) ICCC
22  FORMAT(1H0,58X,*ICCC = *,I10)
180  N1=N2+1
190  N2=N1+IUDATA(NP(I))-1
C
C      200 CONTINUE
C
C      PRINT RESOURCE USAGE DURING BASE YEAR
      M=RNUM
      RTIME=RTIME/360.
      WRITE(6,24) TINITL,RTIME
24  FORMAT(1H1,34X,*RESOURCE USAGE BETWEEN YEARS *,F9.2,* AND *,
      * F9.2///35X,*RESOURCE*,8X,*MEAN*,4X,*STANDARD*,5X,*MAXIMUM*,
      * 2X,*95 PERCENT*/37X,*NUMBER*,7X,*VALUE*,3X,*DEVIATION*,7X,
      * *VALUE*,2X,*CONSTRAINT*)
      DO 300 IK=1,MRES
      CALL CALST(RBAR,RST,IK,M,RSUM,RSQ)
      CONSTR=RBAR+1.96*RST
300  WRITE(6,25) IK,RBAR,RST,RMAX(IK),CONSTR
25  FORMAT(1H0,32X,I10,4F12.2)
      WRITE(6,26) M
26  FORMAT(1H0,34X,*THE NUMBER OF OBSERVATIONS (MONTHS) IS*,I5)
C
      WRITE(6,17)
17  FORMAT(1H1)
C
1800 RETURN
      END

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